A New Immersion and Invariance Control and Stable Deep Learning Fuzzy Approach for Power/Voltage Control Problem

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This work was supported by the Taif University Researchers Supporting Project under Grant TURSP-2020/266 of Taif University, Taif, Saudi Arabia; and in part by the Brazilian Agency CAPES.

ABSTRACT Background: The use of renewable energies is extended due to their valuable features such as abundant and clarity. The microgrids that include the renewable energies are widely used in various applications such as power supplying of remote areas, increasing the network reliability, reducing the greenhouse gas emission, reducing the consumption demand, eliminating the consumption peaks, and so on. But, energy management in the these systems in an challenging problem. Because, there are some natural perturbations such as variation output load, grid-side faults and changes of irradiation and temperature. Aim and Objective: The problem is to design a controller to regulate the output voltage/energy under aforementioned disturbances. Methods: The paper presents a new approach for energy management in Photovoltaic (PV)/Battery/Fuel Cells (FC) systems. The uncertainties are compensated by the new optimization rules based on Immersion and Invariance (I&I) theorem and proposed deep learning type-2 fuzzy logic compensator (T2FLC). The objective function of T2FLC is to minimize the tracking error in presence of perturbations. The adaptation rules are derived such that the I&I stabilization criterions are satisfied. Both rules and fuzzy sets (FSs) of T2FLCs are optimized by guaranteed stability rules to tackle the effect of perturbations and estimation errors. Results and Discussion: It is shown that a well voltage/energy regulation performance is achieved under variation of temperature, suddenly changes of load and variation of irradiation. A comparison with similar controllers demonstrates the superiority of the suggested approach. Conclusion: The suggested regulator do not depend on the mathematical models, and results in good accuracy under difficult conditions, then it can be used in various applications.

INDEX TERMS Energy management, immersion and invariance, deep learning, fuzzy systems, voltage control, stability.

I. INTRODUCTION

The energy management in microgrids including renewable energies has became one of the interesting topics in past decade. The dynamics of the hybrid systems that contains PVs, FCs and batteries are always disturbed by nature factors such as variation output load, grid-side faults and changes of irradiation and temperature. The designing of strong control systems to kept output voltage and power in a desired level is one of the challenging problems [1]–[4]. Many control systems have been presented for power and voltage regulation. For example, the power fluctuation is
studied in [5], and a balancing controller is proposed. In [6], a predictive controller is presented to cope with the effect of variation of electricity tariff and irradiation. In [7], an energy management technique is designed by battery charging control scheme to reduce the operating cost. In [8], the dynamics of PV panels and batteries are modeled and then a control system is suggested for stabilizing output voltage. In [9], a multi-objective controller is developed to regulate output voltage under nonlinear output load. The mode-triggered droop controller is designed in [10] for energy management, and its energy distribution capability is examined in various conditions. In [11], a multifunctional controller is developed, the problem of harmonics mitigation is investigated, and improvement of the power quality is shown. In [12], a distributed control method is suggested for power regulation, and robustness against time delays is studied. The coordinated control scheme is developed in [13], to improve the battery life.

To tackle the effect of perturbations and dynamic uncertainties, some fuzzy and neural controllers have been developed [14]. For example, a fuzzy logic controller (FLC) is introduced in [15], and the superiority of FLC is shown under fluctuation of PV power. In [16], the fluctuation of the output load is taken to account, and the efficiency improvement by FLC is shown. In [17], a FLC is designed to make an energy balance between PV and FC, and the parameters of FLC are optimized by genetic algorithm. The energy management is studied by cuckoo algorithm in [18], to compensate PV power shortage in necessary times. In [19], a FLC is proposed to handle the uncertain dynamics of PV and FCs, and by comparison with conventional controllers the good proficiency of FLCs is demonstrated. The effect of fast load variation is studied in [20] by designing an FLC, and it is shown that energy consumption is decreased about 19.6%. In [19], the dynamic perturbation by variation of temperature is studied and an FLC is designed. The PV and FC dynamic modeling is studied in [21], and a simple FLC is suggested for application in electric vehicles. The optimization of hydrogen production is investigated in [22] by FLC, and the superiority of FLCs in term of less required expertise is discussed. Compass of various approaches in reviewed in [23].

Recently, the better capability of type-2 FLCs and deep learning algorithms have been shown in various problems such as internet of things [24], wireless sensor networks [25], robotics [26], clustering problems [27], power systems [28], electrical vehicles [29], control systems [30], and so on. However, this type of FLCs with guaranteed stability have been rarely studied. In [31], a high-order FLC is presented for estimation of uncertainties in PV and battery dynamics. In [32], a T2FLC is developed to cope with irradiation fluctuations. The main drawback of aforementioned studies is that, only rule parameters are optimized, and the antecedent parameters are neglected. Also, the online stability guarantee in the most of presented controllers needs more investigation. In current paper, we present the novel adaptation laws for uncertain parameters based on I&I theorem. The effect of disturbances such as variation of temperature, fluctuation of irradiation and changes of output load are compensated by the suggested deep learning T2FLC by guaranteed stability. The main contributions and the advantages of the suggested method are:

- The novel adaptation laws are presented for uncertain parameters based on I&I theorem.
- The effect of disturbances such as variation of temperature, fluctuation of irradiation and changes of output load are compensated.
- A deep learning T2FLC by guaranteed stability is presented.
- Both rules and FS parameters are optimized.
- The superiority of the designed method is examined under various conditions and comparison with other conventional approaches.

II. PROBLEM FORMULATION

A. GENERAL VIEW

The designed control scheme is depicted in Fig. 1. The dynamics are considered to be uncertain. The adaptation rules are derived by the I&I stabilization approach. The perturbations are compensated by the suggested T2FLC. As shown in Fig. 1, unlike the conventional studies [33]–[35], the adaptation laws are derived form I&I stabilization approach. The main uncertain parameters are estimated by the extracted adaptation laws. Then, the estimation error is taken into account, and a T2FLC is designed. The rules of T2FLC are optimized such that the effect of estimation error is eliminated.

B. FUEL CELL

Today, the role of new and renewable energy sources in the production of electricity is not hidden from anyone. In addition to solar, wind, geothermal and biomass energy, fuel cell energy has also become very important. A fuel cell (FC) is a device that generates electricity through a chemical reaction. All fuel cells have two electrical poles (electrodes) called anodes and cathodes. In fact, chemical reactions take place...
in these electrodes, leading to the generation of electricity. In addition, each FC has an electrolyte and a catalyst; The role of the electrolyte is to move charged particles between the electrodes, while the catalyst speeds up the reactions at the electrodes. Although hydrogen is the main fuel, oxygen is also needed to form the reaction. One of the biggest superiorities of an FC is that it generates electricity with the least amount of pollution. In fact, most of the oxygen and hydrogen entering the cell is eventually released as a harmless by-product, water. An FC generates a very small amount of direct current, which is why a large number of cells are used to generate electricity in large batches called stacks.

The dynamics of FC are given as
\[
\begin{align*}
\dot{V}_{FC} &= -u_{FC} \\
&+ \left( \ln \left( \frac{Q_{H_2} - 2\tau_I_{FC}}{k_{H_2} + s} \right) \right) (T_{\text{in}}/2F) + E_0 \right) N_0 \\
\end{align*}
\]

where, \( i_{ph} \) denotes PV/battery currents and \( V_c \) represents the load voltage.

### D. PV MODELING

By the use of single-diode method \([36]\), the dynamics of PV are given as:
\[
\begin{align*}
i_{ph} &= s (k_i (T - T_i) + i_{sc}) \\
I_p &= G \cdot i_{ph} \\
&- \exp \left( \frac{Q (V_p + I_p n_{shg})}{nT_{k_b} - 1} \right) i_o \\
&- \left( I_p n_{shg} + V_p \right) / n_{shg} \\
i_0 &= e^{\left( \frac{T + 273}{T_i + 273} \right) i_{ph}} \left( T + 273 \right)^3 i_i \\
\end{align*}
\]

where, all parameters descriptions are given in Table 5 in Appendix.

### E. BATTERY MODELING

The dynamics of battery are written as \([36]\):
\[
E(t) = - \int \alpha V_{boc} I_b + E_{Loss} dt \\
\alpha = \begin{cases} 
\alpha_1 I_b \geq 0 \\
\alpha_2 I_b < 0, \end{cases} \\
V_b = \frac{V_{boc} - I_b \cdot t_b}{\text{SoC}(t)} = E(t)/E_{Max} \\
\]

The parameter descriptions are given in Table 6, in Appendix.

### III. TYP-2 FLC

The type-2 FLs are the generalization of type-1 counterparts which can support more level of uncertainties. A type-2 fuzzy set has three dimensions, which its third dimension represents the secondary membership. In other words, in type-2 fuzzy sets, the memberships are not crisp values but they are fuzzy numbers. As mentioned earlier, in the power/voltage control problem of microgrids, we face a large number of perturbations, and we need a strong tool to tackle the effect of various disturbances such as dynamic uncertainties, estimation errors of adaptation rules, variation of output load, grid-side faults and changes of irradiation and temperature. Then we formulate a type-2 fuzzy compensator. The structure is given
The memberships for are obtained as:

\[ \Psi_{\theta_{X}}(\chi(t)) = \exp \left( -\frac{(\chi(t) - M_{\theta_{X}})^2}{\alpha_{\theta_{X}}^2} \right) \]

(15)

\[ \Psi_{\delta_{X}}(\chi(t)) = \exp \left( -\frac{(\chi(t) - M_{\delta_{X}})^2}{\alpha_{\delta_{X}}^2} \right) \]

(16)

where, \( M_{\theta_{X}} \) and \( M_{\delta_{X}} \) are the centers of MFs \( \tilde{\theta}_X \) and \( \tilde{\delta}_X \), respectively. \( \alpha_{\theta_{X}} / \alpha_{\delta_{X}} \) is the upper/lower width of \( \tilde{\theta}_X \). \( \alpha_{\theta_{X}} / \alpha_{\delta_{X}} \) is the upper/lower width of \( \tilde{\delta}_X \). Similarly for the input \( \frac{d\chi}{dt} \) we have:

\[ \tilde{\Psi}_{\delta_{X}} \left( \frac{d\chi}{dt} (t) \right) = \exp \left( -\frac{\left( \frac{d\chi}{dt} (t) - M_{\delta_{dx}} \right)^2}{\alpha_{\delta_{dx}}^2} \right) \]

(17)

\[ \tilde{\Psi}_{\theta_{X}} \left( \frac{d\chi}{dt} (t) \right) = \exp \left( -\frac{\left( \frac{d\chi}{dt} (t) - M_{\theta_{dx}} \right)^2}{\alpha_{\theta_{dx}}^2} \right) \]

where, \( M_{\theta_{dx}} \) and \( M_{\delta_{dx}} \) are the centers of MFs \( \tilde{\theta}_{dx} \) and \( \tilde{\delta}_{dx} \), respectively. \( \alpha_{\theta_{dx}} / \alpha_{\delta_{dx}} \) is the upper/lower width of \( \tilde{\theta}_{dx} \). \( \alpha_{\theta_{dx}} / \alpha_{\delta_{dx}} \) is the upper/lower width of \( \tilde{\delta}_{dx} \). The computations are as: 1) The inputs are tracking error \( \chi(t) \), derivative of tracking error \( \frac{d\chi(t)}{dt} \) and integral of tracking error \( \int_0^t \chi(y) dy \). 2) The memberships are obtained as:

\[ \tilde{\Psi}_{\theta_{X}} \left( \frac{d\chi}{dt} (t) \right) = \exp \left( -\frac{\left( \frac{d\chi}{dt} (t) - M_{\theta_{dx}} \right)^2}{\alpha_{\theta_{dx}}^2} \right) \]

(18)

\[ \tilde{\Psi}_{\delta_{X}} \left( \frac{d\chi}{dt} (t) \right) = \exp \left( -\frac{\left( \frac{d\chi}{dt} (t) - M_{\delta_{dx}} \right)^2}{\alpha_{\delta_{dx}}^2} \right) \]

(18)

where, \( M_{\theta_{dx}} \) and \( M_{\delta_{dx}} \) are the centers of MFs \( \tilde{\theta}_{dx} \) and \( \tilde{\delta}_{dx} \), respectively. \( \alpha_{\theta_{dx}} \) and \( \alpha_{\delta_{dx}} \) are the upper and lower width of \( \tilde{\theta}_{dx} \). \( \alpha_{\theta_{dx}} / \alpha_{\delta_{dx}} \) is the upper/lower width of \( \tilde{\delta}_{dx} \). Finally, for input \( \int_0^t \chi(y) dy \), the memberships are:

\[ \tilde{\Psi}_{\theta_{X}} \left( \int_0^t \chi(y) dy \right) = \exp \left( -\frac{\left( \int_0^t \chi(y) dy - M_{\theta_{x}} \right)^2}{\alpha_{\theta_{x}}^2} \right) \]

(19)

\[ \tilde{\Psi}_{\delta_{X}} \left( \int_0^t \chi(y) dy \right) = \exp \left( -\frac{\left( \int_0^t \chi(y) dy - M_{\delta_{x}} \right)^2}{\alpha_{\delta_{x}}^2} \right) \]

(20)

where, \( M_{\theta_{x}} \) and \( M_{\delta_{x}} \) are the centers of MFs \( \tilde{\theta}_x \) and \( \tilde{\delta}_x \), respectively. \( \alpha_{\theta_{x}} / \alpha_{\delta_{x}} \) is the upper/lower width of \( \tilde{\theta}_x \). \( \alpha_{\theta_{x}} / \alpha_{\delta_{x}} \) is the upper/lower width of \( \tilde{\delta}_x \). The rules firing are obtained as:

\[ \tilde{\theta}_1 = \Psi_{\theta_{X}} \left( \chi(t) \right) \cdot \tilde{\Psi}_{\theta_{X}} \left( \frac{d\chi}{dt} (t) \right) \cdot \tilde{\Psi}_{\theta_{X}} \left( \int_0^t \chi(y) dy \right) \]

\[ \tilde{\theta}_2 = \Psi_{\delta_{X}} \left( \chi(t) \right) \cdot \tilde{\Psi}_{\delta_{X}} \left( \frac{d\chi}{dt} (t) \right) \cdot \tilde{\Psi}_{\delta_{X}} \left( \int_0^t \chi(y) dy \right) \]
The output is computed as:

\[ u_c (z | X) = \frac{\sum_{i=1}^{N} z_i \left( \theta_i + \bar{\theta}_i \right)}{\sum_{i=1}^{N} \bar{\theta}_i + \bar{\theta}_i} \]  

(23)

IV. I&I ADAPTATION LAWS

In this section the main tuning rules are presented and the stability is investigated. Unlike the most conventional studies, the tuning rules are extracted from I&I stability analysis. The tuning rules for uncertain parameters are considered such that all criteria of I&I theorem are satisfied. Following, the details are given in Theorem 1. Before, the presenting the Theorem 1, the main I&I Lemma is given as:

**Lemma 1 (I&I Stabilization [37])**: Consider the dynamics of under control plant as:

\[ \dot{\mu} = F (\mu) + H (\mu) u \]  

(26)

where, \( F (\mu) \) and \( H (\mu) \) are nonlinear functions with unknown parameters \( \mu \) and equilibrium point \( \mu^e \). The system (26) is I&I stabilizable, if there is \( \alpha_1 \) and \( \alpha_2 \) such that all trajectories of (27):

\[ \dot{x} = F (\mu) + H (\mu) u(\mu, \hat{\mu} + \alpha_1 (\mu)) \]

\[ \frac{d\hat{\mu}}{dt} = \alpha_2 (\mu, \hat{\mu}) \]  

(27)

are staying on:

\[ \varphi = \{ (\mu, \mu) | \hat{\mu} - \mu + \alpha_1 (\mu) = 0 \} \]  

(28)

Our results are given in the Theorem 1.

**Theorem 1**: By the controllers (29-30) and adaptation rules (31-33) the stability is ensured.

\[ u_p = \frac{1}{\mu_2} \left[ (r_1 + \lambda_1 \chi) (\hat{L} \mu + \eta \hat{L} \mu (\chi)) + \mu_2 - V_p (\mu_1) \right] \]  

(29)

\[ u_p = \frac{1}{\mu_3} \left[ (r_2 + \lambda_2 \chi) (\hat{C} + \eta \hat{C} (\chi)) - \mu_1 + \mu_2 / (\hat{R} \eta + \hat{R} (\chi) + \mu_1 \mu_p) \right] \]  

(30)

\[ \dot{\hat{L}} = \frac{\partial \hat{L} \mu (\chi)}{\partial \chi_1} \lambda_1 \chi_1 + \frac{\partial \hat{L} \mu (\chi)}{\partial \chi_2} \lambda_2 \chi_2 \]  

(31)

\[ \dot{\hat{R}} = \frac{\partial \hat{R} \mu (\chi)}{\partial \chi_1} \lambda_1 \chi_1 + \frac{\partial \hat{R} \mu (\chi)}{\partial \chi_2} \lambda_2 \chi_2 \]  

(32)

\[ \dot{\hat{C}} = \frac{\partial \hat{C} \mu (\chi)}{\partial \chi_1} \lambda_1 \chi_1 + \frac{\partial \hat{C} \mu (\chi)}{\partial \chi_2} \lambda_2 \chi_2 \]  

(33)

where, \( r_i \) represents the reference signal for outputs \( \mu_i \) and:

\[ \frac{\partial \hat{L} \mu (\chi)}{\partial \chi_1} = r_1 + \lambda_1 \chi_1 \]  

(34)

\[ \frac{\partial \hat{L} \mu (\chi)}{\partial \chi_2} = 0 \]  

(35)

\[ \frac{\partial \hat{R} \mu (\chi)}{\partial \chi_1} = 0 \]  

(36)
where, $\lambda_i$ and $\eta$ are constant and $\chi_i$, $i=1,2$ are defined as:
\[
\begin{align*}
\chi_1 & \overset{\Delta}{=} r_1 - \mu_1 \\
\chi_2 & \overset{\Delta}{=} r_2 - \mu_2
\end{align*}
\]
(40)

Proof: The dynamics are estimated as:
\[
\begin{align*}
\dot{\mu}_1 &= (-\mu_2 + V_p(\mu_1) + \mu_2 u_p) / L_p \\
\dot{\mu}_2 &= \frac{1}{C} \left( \mu_1 - \mu_2 / \hat{R} + \mu_3 u_b - \mu_1 u_p \right) \\
\dot{\mu}_3 &= (-\mu_2 u_b + V_b(\mu_3)) / L_b
\end{align*}
\]
(41)

The reference dynamics are assumed to be:
\[
\begin{align*}
\dot{\chi}_1 &= -\lambda_1 \chi_1 \\
\dot{\chi}_2 &= -\lambda_2 \chi_2
\end{align*}
\]
(42)

Time derivative of (40), gives:
\[
\begin{align*}
\dot{\chi}_1 &= \dot{\dot{\chi}}_1 - \dot{\mu}_1 \\
\dot{\chi}_2 &= \dot{\dot{\chi}}_2 - \dot{\mu}_2
\end{align*}
\]
(43)

By substituting of $\dot{\mu}_i$, equation (43) becomes:
\[
\begin{align*}
\dot{\chi}_1 &= \dot{\dot{\chi}}_1 - (-\mu_2 + V_p(\mu_1) + \mu_2 u_p(\chi, L_p)) / L_p \\
\dot{\chi}_2 &= \dot{\dot{\chi}}_2 - \frac{1}{C} \left( \mu_1 - \mu_2 / R + \mu_3 u_b(\chi, C, R) - \mu_1 u_p \right)
\end{align*}
\]
(44)

Considering Lemma 1, (44) is extended as:
\[
\begin{align*}
\dot{\chi}_1 &= \dot{\dot{\chi}}_1 - \left( -\mu_2 + V_p(\mu_1) + \mu_2 u_p(\chi, \hat{L}_p + \eta \hat{L}_p(\chi)) \right) / L_p \\
\dot{\chi}_2 &= \dot{\dot{\chi}}_2 - \frac{1}{C} \left( \mu_1 - \mu_2 / R + \mu_3 u_b(\chi, \hat{C} + \eta \hat{C}(\chi), \hat{R} + \eta \hat{R}(\chi)) - \mu_1 u_p \right)
\end{align*}
\]
(45)

where,
\[
\begin{align*}
\hat{L}_p &= \psi_L(\chi, \hat{L}_p) \\
\hat{R} &= \psi_R(\chi, \hat{R}) \\
\hat{C} &= \psi_C(\chi, \hat{C}) \\
\hat{\chi} &= [\chi_1, \chi_2]^T
\end{align*}
\]
(46-49)

where, $\hat{L}_p$, $\hat{R}$ and $\hat{C}$ are the estimation of $L_p$, $R$ and $C$. The system (45), is I&I stabilizable if there exist $\hat{L}_p$, $\hat{R}$, $\psi_R$, $\psi_L$, $\psi_C$, such that:
\[
\varphi_L = \left\{ (\chi, L_p) \in \Re^{n+1} \big| \hat{L}_p + \eta \hat{L}_p(\chi) - \hat{L}_p = 0 \right\}
\]
(50)

\[
\begin{align*}
\varphi_R &= \left\{ (\chi, R) \in \Re^{n+1} \big| \hat{R} + \eta \hat{R}(\chi) - R = 0 \right\} \\
\varphi_C &= \left\{ (\chi, C) \in \Re^{n+1} \big| \hat{C} + \eta \hat{C}(\chi) - C = 0 \right\}
\end{align*}
\]
(51-52)

where, $n = 2$ and $\eta$ is a constant. To satisfy (50-52), the stability of the following errors should be ensured:
\[
\begin{align*}
e_p &= \hat{L}_p + \eta \hat{L}_p(\chi) - L_p \\
e_R &= \hat{R} + \eta \hat{R}(\chi) - R \\
e_C &= \hat{C} + \eta \hat{C}(\chi) - C
\end{align*}
\]
(53-55)

Form (53-55), the equation (44) is rewritten as:
\[
\begin{align*}
\hat{\dot{\chi}}_1 &= \dot{\chi}_1 - \dot{\dot{\chi}}_1 = -(-\mu_2 + V_p(\mu_1) + \mu_2 u_p) / (\hat{L}_p + \eta \hat{L}_p(\chi) - e_p) \\
\hat{\dot{\chi}}_2 &= \dot{\chi}_2 - \frac{1}{\hat{C} + \eta \hat{C}(\chi) - e_C} \left[ -\mu_2 / (\hat{R} + \eta \hat{R}(\chi) - e_R) + \mu_2 / (\hat{R} + \eta \hat{R}(\chi)) \right]
\end{align*}
\]
(56)

By applying controllers (29-30) on (56), we have:
\[
\begin{align*}
\hat{\dot{\chi}}_1 &= \hat{\dot{\chi}}_1 - \frac{1}{\hat{L}_p + \eta \hat{L}_p(\chi) - e_p} \left[ -\mu_2 / (\hat{R} + \eta \hat{R}(\chi) - e_R) + \mu_2 / (\hat{R} + \eta \hat{R}(\chi)) \right] \\
\hat{\dot{\chi}}_2 &= \hat{\dot{\chi}}_2 - \frac{1}{\hat{C} + \eta \hat{C}(\chi) - e_C} \left[ -\mu_2 / (\hat{R} + \eta \hat{R}(\chi) - e_R) + \mu_2 / (\hat{R} + \eta \hat{R}(\chi)) \right]
\end{align*}
\]
(57-58)

Equations (57-58), can be simplified as:
\[
\begin{align*}
\hat{\dot{\chi}}_1 &= \hat{\dot{\chi}}_1 - \frac{1}{\hat{L}_p + \eta \hat{L}_p(\chi) - e_p} \left[ -\mu_2 / (\hat{R} + \eta \hat{R}(\chi) - e_R) + \mu_2 / (\hat{R} + \eta \hat{R}(\chi)) \right] \\
\hat{\dot{\chi}}_2 &= \hat{\dot{\chi}}_2 - \frac{1}{\hat{C} + \eta \hat{C}(\chi) - e_C} \left[ -\mu_2 / (\hat{R} + \eta \hat{R}(\chi) - e_R) + \mu_2 / (\hat{R} + \eta \hat{R}(\chi)) \right]
\end{align*}
\]
(59-60)

From (59-60), we have:
\[
\begin{align*}
\hat{\dot{\chi}}_1 &= \hat{\dot{\chi}}_1 - \frac{(\hat{\dot{r}}_1 + \lambda_1 \chi_1) e_p}{\hat{L}_p + \eta \hat{L}_p(\chi) - e_p} \\
\hat{\dot{\chi}}_2 &= \hat{\dot{\chi}}_2 - \frac{(\hat{\dot{r}}_2 + \lambda_2 \chi_2) e_C}{\hat{C} + \eta \hat{C}(\chi) - e_C}
\end{align*}
\]
(61-62)

Form (53-55), time derivative of $e_p$, $e_R$ and $e_C$ are computed as:
\[
\hat{\dot{e}}_p = \frac{\partial \hat{L}_p(\chi)}{\partial \chi_1} \hat{\dot{\chi}}_1 + \frac{\partial \hat{L}_p(\chi)}{\partial \chi_2} \hat{\dot{\chi}}_2
\]
(63)
\( \dot{e}_R = \dot{R} + \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_1} \dot{\chi}_1 + \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_2} \dot{\chi}_2 \) \hspace{1cm} (64)

\( \dot{e}_C = \dot{C} + \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_1} \dot{\chi}_1 + \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_2} \dot{\chi}_2 \) \hspace{1cm} (65)

Substituting \( \dot{\chi}_1 \) and \( \dot{\chi}_2 \), yields:

\( \dot{e}_P = \dot{L}_P + \eta \frac{\partial \hat{L}_P(\chi)}{\partial \chi_1} \left[ -\lambda_1 \dot{\chi}_1 - \frac{(\dot{r}_1 + \lambda_1 \chi_1) e_P}{L_P + \eta L_P(\chi) - e_P} \right] + \eta \frac{\partial \hat{L}_P(\chi)}{\partial \chi_2} \left[ -\lambda_2 \dot{\chi}_2 - \frac{\mu_2 e_R}{(C + \eta \hat{C}(\chi) - e_C)(R + \eta \hat{R}(\chi))} \right] + \eta \frac{\partial \hat{L}_P(\chi)}{\partial \chi_2} \left[ (\dot{r}_2 + \lambda_2 \chi_2) e_C \right] \) \hspace{1cm} (66)

\( \dot{e}_R = \dot{R} + \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_1} \left[ -\lambda_1 \dot{\chi}_1 - \frac{(\dot{r}_1 + \lambda_1 \chi_1) e_P}{L_P + \eta L_P(\chi) - e_P} \right] + \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_2} \left[ -\lambda_2 \dot{\chi}_2 - \frac{\mu_2 e_R}{(C + \eta \hat{C}(\chi) - e_C)(R + \eta \hat{R}(\chi))} \right] + \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_2} \left[ (\dot{r}_2 + \lambda_2 \chi_2) e_C \right] \) \hspace{1cm} (67)

\( \dot{e}_C = \dot{C} + \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_1} \left[ -\lambda_1 \dot{\chi}_1 - \frac{(\dot{r}_1 + \lambda_1 \chi_1) e_P}{L_P + \eta L_P(\chi) - e_P} \right] + \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_2} \left[ -\lambda_2 \dot{\chi}_2 - \frac{\mu_2 e_R}{(C + \eta \hat{C}(\chi) - e_C)(R + \eta \hat{R}(\chi))} \right] + \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_2} \left[ (\dot{r}_2 + \lambda_2 \chi_2) e_C \right] \) \hspace{1cm} (68)

From (66-68), \( \dot{L}_P \) and \( \dot{R} \) and \( \dot{C} \) are considered as given in (31-33). From (31-33), \( \dot{e}_P \), \( \dot{e}_R \) and \( \dot{e}_C \) in (66-68), become:

\( \dot{e}_P = \eta \frac{\partial \hat{L}_P(\chi)}{\partial \chi_1} \left[ -\frac{(\dot{r}_1 + \lambda_1 \chi_1) e_P}{L_P + \eta L_P(\chi) - e_P} \right] + \eta \frac{\partial \hat{L}_P(\chi)}{\partial \chi_2} \left[ -\frac{\mu_2 e_R}{(C + \eta \hat{C}(\chi) - e_C)(R + \eta \hat{R}(\chi))} \right] + \eta \frac{\partial \hat{L}_P(\chi)}{\partial \chi_2} \left[ (\dot{r}_2 + \lambda_2 \chi_2) e_C \right] \) \hspace{1cm} (69)

\( \dot{e}_R = \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_1} \left[ -\frac{(\dot{r}_1 + \lambda_1 \chi_1) e_P}{L_P + \eta L_P(\chi) - e_P} \right] + \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_2} \left[ -\frac{\mu_2 e_R}{(C + \eta \hat{C}(\chi) - e_C)(R + \eta \hat{R}(\chi))} \right] + \eta \frac{\partial \hat{R}(\chi)}{\partial \chi_2} \left[ (\dot{r}_2 + \lambda_2 \chi_2) e_C \right] \) \hspace{1cm} (70)

\( \dot{e}_C = \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_1} \left[ -\frac{(\dot{r}_1 + \lambda_1 \chi_1) e_P}{L_P + \eta L_P(\chi) - e_P} \right] + \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_2} \left[ -\frac{\mu_2 e_R}{(C + \eta \hat{C}(\chi) - e_C)(R + \eta \hat{R}(\chi))} \right] + \eta \frac{\partial \hat{C}(\chi)}{\partial \chi_2} \left[ (\dot{r}_2 + \lambda_2 \chi_2) e_C \right] \) \hspace{1cm} (71)

From (69-71), \( \dot{L}_P(\chi) \), \( \dot{R}(\chi) \) and \( \dot{C}(\chi) \) should be determined such that the dynamics of \( \dot{e}_P \), \( \dot{e}_R \) and \( \dot{e}_C \) to be stable. Then we have:

\( \frac{\partial \dot{L}_P(\chi)}{\partial \chi_1} = \dot{r}_1 + \lambda_1 \chi_1 \) \hspace{1cm} (72)

\( \frac{\partial \dot{L}_P(\chi)}{\partial \chi_2} = 0 \) \hspace{1cm} (73)

\( \frac{\partial \dot{R}(\chi)}{\partial \chi_1} = 0 \) \hspace{1cm} (74)

\( \frac{\partial \dot{R}(\chi)}{\partial \chi_2} = 0 \) \hspace{1cm} (75)

\( \frac{\partial \dot{C}(\chi)}{\partial \chi_1} = 0 \) \hspace{1cm} (76)

\( \frac{\partial \dot{C}(\chi)}{\partial \chi_2} = \dot{r}_2 + \lambda_2 \chi_2 \) \hspace{1cm} (77)

From (72-77), the dynamics of \( \dot{e}_P \), \( \dot{e}_R \) and \( \dot{e}_C \) in (69-71), become:

\( \dot{e}_P = -\eta \frac{1}{L_P + \eta L_P(\chi) - e_P} \left[ (\dot{r}_1 + \lambda_1 \chi_1) e_P \right] \) \hspace{1cm} (78)

\( \dot{e}_R = -\eta \frac{1}{C + \eta \hat{C}(\chi) - e_C} \left[ \frac{1}{R + \eta \hat{R}(\chi)} \right] \cdot \frac{1}{R + \eta \hat{R}(\chi)} \cdot \frac{\mu_2 e_R}{(\dot{r}_2 + \lambda_2 \chi_2) e_C} \) \hspace{1cm} (79)

\( \dot{e}_C = -\eta \frac{1}{C + \eta \hat{C}(\chi) - e_C} \left[ (\dot{r}_2 + \lambda_2 \chi_2) e_C \right] \) \hspace{1cm} (80)

To show that the dynamics of \( \dot{e}_P \), \( \dot{e}_R \) and \( \dot{e}_C \) in (78-80) are stable, the following Lyapunov is considered:

\( V = \frac{1}{2} e_P^2 + \frac{1}{2} e_R^2 + \frac{1}{2} e_C^2 \) \hspace{1cm} (81)

Time derivative of (81), gives:

\( \dot{V} = e_P \dot{e}_P + e_R \dot{e}_R + e_C \dot{e}_C \) \hspace{1cm} (82)

substituting from (78-80), \( \dot{V} \) in (82), becomes:

\( \dot{V} = -\eta \frac{(\dot{r}_1 + \lambda_1 \chi_1)^2}{L_P + \eta L_P(\chi) - e_P} e_P^2 \) \hspace{1cm} (83)
\[ \dot{V} = -[e_p \ e_R \ e_C] \Psi \begin{bmatrix} e_p \\ e_R \\ e_C \end{bmatrix} \] (84)

where,
\[
\Psi_{11} = \eta \frac{(\dot{r}_1 + \lambda_1 \chi_1)^2}{\dot{L}_p + \eta \dot{L}_p(\chi) - e_p}
\]
\[
\Psi_{12} = \frac{1}{\dot{C} + \eta \dot{C}(\chi) - e_C} \left( \frac{1}{\dot{R} + \eta \dot{R}(\chi)} + \frac{1}{\dot{R} + \eta \dot{R}(\chi)} \right)
\]
\[
\Psi_{22} = \eta \frac{(\dot{r}_2 + \lambda_2 \chi_2)^2}{\dot{C} + \eta \dot{C}(\chi) - e_C} \cdot (\dot{r}_2 + \lambda_2 \chi_2)^2
\]

From the fact that:
\[
C = \dot{C} + \eta \dot{C}(\chi) - e_C > 0
\]
\[
R = \dot{R} + \eta \dot{R}(\chi) - e_R > 0
\]
\[
L_p = \dot{L}_p + \eta \dot{L}_p(\chi) - e_p > 0
\]

It is concluded that by properly choosing \( \lambda_1 \) and \( \lambda_2 \), \( \Psi \) is positive definite and then the dynamics of \( \dot{e}_p \), \( \dot{e}_R \) and \( \dot{e}_C \) are stable.

**V. DEEP LEARNED TYPE-2 FUZZY COMPENSATOR**

To ensure the stability in versus of I&I approximation error an AT2FLC is presented. The outcomes are given in Theorem 2.

**Theorem 2:** The stability of the tracking error dynamics (61-62) is ensued in versus of I&I approximation error and dynamic perturbation by the following modified controllers and tuning rules of AT2FLCs:

\[
u_{p} = \frac{1}{\mu_2} \left[ (\dot{r}_1 + \lambda_1 \chi_1) \left( \dot{L}_p + \eta \dot{L}_p(\chi) \right) \right]
\]
\[
u_{b} = \frac{1}{\mu_3} \left[ (\dot{r}_2 + \lambda_2 \chi_2) \left( \dot{C} + \eta \dot{C}(\chi) \right) - \mu_1 u_p + u_c b(z_b | X_b) \right]
\]
\[
\hat{z}_p = \gamma \pi_p \chi_1
\]
\[
\hat{z}_b = \gamma \pi_b \chi_2
\]

where, \( u_{cp}(z_p | X_p) \) and \( u_{cb}(z_b | X_b) \) are AT2FLCs. \( \gamma \) is a constant.

Proof: To deeply train the fuzzy compensator by Lyapunov approach, the outputs \( u_{cp}(z_p | X_p) \) and \( u_{cb}(z_b | X_b) \) (see (23)) are written as:

\[
\begin{align*}
u_{cp}(z_p | X_p) &= z_T^p \pi_p \\
u_{cb}(z_b | X_b) &= z_T^b \pi_b
\end{align*}
\]

where, \( z_T^p \) and \( z_T^b \) are vector of tuneable parameters which include both rule (consequent) parameters (\( z_{pc}^p \), \( z_{bc}^p \)) and centers of FSs (antecedent parameters: \( z_{pa}^p \), \( z_{ba}^p \));

\[
\begin{align*}
\pi_p^T &= \begin{bmatrix} \pi_{pa}^T & \pi_{pc}^T \end{bmatrix} \\
\pi_b^T &= \begin{bmatrix} \pi_{ba}^T & \pi_{bc}^T \end{bmatrix}
\end{align*}
\]

\( \pi_p^T \) and \( \pi_b^T \) are written as:

\[
\begin{align*}
\pi_p^T &= \begin{bmatrix} \theta_{p1} \theta_{p2} \ldots \theta_{pN} \end{bmatrix}^T \\
\pi_b^T &= \begin{bmatrix} \theta_{b1} \theta_{b2} \ldots \theta_{bN} \end{bmatrix}^T
\end{align*}
\]

where,

\[
\begin{align*}
\pi_p^T &= \frac{1}{\sum_{i=1}^{N} \theta_{pi} + \theta_{bi}} \\
\pi_b^T &= \frac{1}{\sum_{i=1}^{N} \theta_{pi} + \theta_{bi}}
\end{align*}
\]

By applying controllers (91-92), the error dynamics become:

\[
\dot{\hat{x}}_1 = -\lambda_1 \chi_1 - \frac{(\dot{r}_1 + \lambda_1 \chi_1 + u_{cp}(z_p | X_p))}{L_p + \eta \dot{L}_p(\chi) - e_p} \\
\dot{\hat{x}}_2 = -\lambda_2 \chi_2 - \frac{1}{\dot{C} + \eta \dot{C}(\chi) - e_C} \\
\times \left[ \frac{(\dot{R} + \eta \dot{R}(\chi)) - e_R}{(\dot{R} + \eta \dot{R}(\chi))} \right]
\]

By adding and subtracting optimal AT2FLCs \( u_{cp}(z_p^* | X_p) \) and \( u_{cb}(z_b^* | X_b) \), the dynamics (100-101) are rewritten as:

\[
\dot{\hat{x}}_1 = -\lambda_1 \chi_1 + u_{cp}(z_p^* | X_p) - u_{cp}(z_p | X_p) \\
- \frac{(\dot{r}_1 + \lambda_1 \chi_1 + u_{cp}(z_p^* | X_p))}{L_p + \eta \dot{L}_p(\chi) - e_p} - u_{cp}(z_p^* | X_p)
\]

\[
\dot{\hat{x}}_2 = -\lambda_2 \chi_2 + u_{cb}(z_b^* | X_b) - u_{cb}(z_b | X_b) - \frac{1}{(\dot{C} + \eta \dot{C}(\chi) - e_C)}
\]

\[\vdots\]
From (104-105), the equations (102-103), are written as:

\[
\hat{\lambda}_1 = -\lambda_1 \chi_1 + \tilde{z}_p \pi_p \\
\frac{1}{L_p + \eta L_p (\chi) - e_p} - u_{cp} (\tilde{z}_p | X_p) \quad (108)
\]

\[
\hat{\lambda}_2 = -\lambda_2 \chi_2 + \tilde{z}_b \pi_b - \frac{1}{\hat{C} + \eta \hat{C} (\chi) - e_c} \times [ \hat{R} + \eta \hat{R} (\chi) - e_R ] \\
\frac{1}{\hat{R} + \eta \hat{R} (\chi) - e_R} - \mu_2 e_R \\
+ (\hat{r}_2 + \lambda_2 \chi_2 + u_{cb} (\tilde{z}_b | X_b)) e_c] - u_{cb} (\tilde{z}_b | X_b) \quad (109)
\]

Consider the following definitions:

\[
\epsilon_p^* = -\frac{(\hat{r}_1 + \lambda_1 \chi_1 + u_{cp} (\tilde{z}_p | X_p)) e_p}{L_p + \eta L_p (\chi) - e_p} - u_{cp} (\tilde{z}_p | X_p) \quad (110)
\]

\[
\epsilon_b^* = -\frac{1}{\hat{C} + \eta \hat{C} (\chi) - e_c} \times [ \hat{R} + \eta \hat{R} (\chi) - e_R ] \\
\frac{1}{\hat{R} + \eta \hat{R} (\chi) - e_R} - \mu_2 e_R \\
+ (\hat{r}_2 + \lambda_2 \chi_2 + u_{cb} (\tilde{z}_b | X_b)) e_c] - u_{cb} (\tilde{z}_b | X_b) \quad (111)
\]

Considering definitions (110-111), equations (108-109), become:

\[
\hat{\lambda}_1 = -\lambda_1 \chi_1 + \tilde{z}_p \pi_p + \epsilon_p^* \quad (112)
\]

\[
\hat{\lambda}_2 = -\lambda_2 \chi_2 + \tilde{z}_b \pi_b + \epsilon_b^* \quad (113)
\]

To investigate the stability, the following Lyapunov is taken to account:

\[
V = \frac{1}{2} \chi_1^2 + \frac{1}{2} \chi_2^2 + \frac{1}{2} \tilde{z}_p^2 + \frac{1}{2} \tilde{z}_b^2 \quad (114)
\]

From (114), \( \dot{V} \) is obtained as:

\[
\dot{V} = \chi_1 \hat{\lambda}_1 + \chi_2 \hat{\lambda}_2 - \frac{1}{\gamma} \tilde{z}_p^2 \hat{\lambda}_p - \frac{1}{\gamma} \tilde{z}_b^2 \hat{\lambda}_b \quad (115)
\]

By substituting (112-113), \( \dot{V} \) becomes:

\[
\dot{V} = \chi_1 (\tilde{z}_p \pi_p + \epsilon_p^*) + \chi_2 (\tilde{z}_b \pi_b + \epsilon_b^*) - \frac{1}{\gamma} \tilde{z}_p^2 \hat{\lambda}_p - \frac{1}{\gamma} \tilde{z}_b^2 \hat{\lambda}_b \quad (116)
\]

\section*{VI. SIMULATION STUDIES}

Several examinations are presented in this section. Simulation condition is described in Table 1.

\begin{table}[h]
\centering
\caption{Simulation condition.}
\begin{tabular}{|c|c|c|}
\hline
Parameter & Value & Parameter & Value \\
\hline
\( L_p \) & 6 (mH) & \( L_b \) & 15 (mH) \\
\( Q \) & 1.60e-19 & \( n \) & 36 \\
\( P_{PV} \) & 55 (w) & \( i_{sc} \) & 3.55 (A) \\
\( C' \) & 500 (\mu f) & \( r_p \) & 30 (m\Omega) \\
\( r_b \) & 80 (m\Omega) & \( k_b \) & 1.38e-23 \\
\( T_c \) & 1.2 & \( \kappa_b \) & 1.5 (A/k) \\
\( A \) & 5.980e-8 (A) & \( V_{loc} \) & 15 (v) \\
\( \beta_1 \) & 0.85 & \( E_g \) & 1.120 (ev) \\
\( \beta_2 \) & 1.15 & \( P_b \) & 20 (w) \\
\hline
\end{tabular}
\end{table}

From tuning rules of AT2FLCs (93-94), \( \dot{V} \) is written as:

\[
\dot{V} = -\lambda_1 \chi_1^2 - \lambda_2 \chi_2^2 + \chi_1 \epsilon_p^* + \chi_2 \epsilon_b^* \\
- \frac{1}{\gamma} \tilde{z}_p^2 \hat{\lambda}_p - \frac{1}{\gamma} \tilde{z}_b^2 \hat{\lambda}_b \quad (117)
\]

The equation (117) is simplified as:

\[
\dot{V} = -\lambda_1 \chi_1^2 - \lambda_2 \chi_2^2 + \chi_1 \epsilon_p^* + \chi_2 \epsilon_b^* \\
+ \frac{1}{\gamma} \tilde{z}_p^2 \hat{\lambda}_p + \chi_2 \epsilon_b^* \quad (118)
\]

From tuning rules of AT2FLCs (93-94), \( \dot{V} \) is written as:

\[
\dot{V} = -\lambda_1 \chi_1^2 - \lambda_2 \chi_2^2 + \chi_1 \epsilon_p^* + \chi_2 \epsilon_b^* \quad (119)
\]

From (119), we have:

\[
\dot{V} \leq -\lambda_1 \chi_1^2 - \lambda_2 \chi_2^2 + \chi_1 \epsilon_p^* + \chi_2 \epsilon_b^* \quad (120)
\]

The \( \epsilon_p^* \) and \( \epsilon_b^* \) are the upper bounds of \( \epsilon_p^* \) and \( \epsilon_b^* \). Then if:

\[
\lambda_1 > \tilde{z}_2^* \\
\lambda_2 > \tilde{z}_b^* \quad (121)
\]

The asymptotically stability is ensured.

\section*{A. SCENARIO 1}

For first evaluation, the irradiation is considered to be varied from 250 to 650 (w/m²) at time \( t = 50s \). Fig. 7, shows that the PV current is well converged to its target level. Fig. 8 demonstrates that the voltage \( V_c \) is kept fixed at its desired level under irradiation disturbances. Fig. 9 shows the well power regulation and finally Figs. 10-11 show the control signals with good shapes and lack of fluctuations.
B. SCENARIO 2
For second evaluation, the irradiation is fixed at 400 (w/m²) and the temperature disturbances is changed from \( T = 15 \) into \( T = 38 (^\circ C) \) at time \( t = 65s \). Fig. 12 shows that the PV current well tracks the reference trajectory. Fig. 13 shows a well resistance in versus of temperature variation. Fig. 14 shows the power regulation, and Figs. 15-16 show the control trajectories.

C. SCENARIO 3
For scenario 3, in the difficult examination situation, the temperature, load and irradiation are changed from \( T = 13 \) to \( T = 48 (^\circ C) \), 60 into 40 (Ω) from 450 into 150 (w/m²), respectively. The disturbances are depicted in Fig. 17. Fig. 18 shows that PV current tracks its optimal trajectory in versus of different perturbations. Fig. 19 reveals that the output voltage strongly tackles the effect of disturbances. Fig. 20 shows a desired power regulation, and finally Figs. 21-22 show the control signal with implementable shapes.

D. COMPARISON
In this section, a comparison is presented with Fractional-order-PID (FO-PID) [38], integral sliding mode controller (SMC) [39], fuzzy PID [40] and intelligent controller by Levy
TABLE 2. RMSE comparison.

| Signal | FO-PID [38] | Integral SMC [39] | Fuzzy PID [40] | ILWO [41] | I&I |
|--------|-------------|-------------------|---------------|-----------|-----|
| $V_C$  | 3.0168      | 1.7208            | 2.3067        | 1.8612    | 1.5006 |

Whale Optimization (ILWO) [41]. The values of root-mean-square-errors (RMSEs) are depicted in Table 2. We see that, the presented I&I method outperforms than other conventional approaches.

**Remark 1:** The main properties of the designed control technique are that: (1) there is no strong dependency on the mathematical models of units, (2) the new adaptation rules which are extracted from I&I stability theorem, well ensure the stability, (3) the designed T2FLC well compensate the approximation error and perturbations, (4) the designed controller shows a good robust efficiency. To examine the robustness, in various scenarios, the irradiation is considered to be varied from 250 to 650 (w/m²), the temperature disturbances is changed from $T = 15$ into $T = 38$ ($\circ$C), the output load is changed from 60 into 40 ($\Omega$), and output power/voltage regulation is evaluated. Simulations show that a good regulation is achieved under aforementioned disturbances and unknown dynamics. Furthermore, a comparison with other conventional approaches such as FO-PID [38], Integral SMC [39], Fuzzy PID [40], and ILWO [41], better reveals the superiority of the suggested I&I-based controller.

**Remark 2:** It should be noted that, in the most of previous conventional learning approaches, it is needed that the learning algorithms to be repeated in some epochs. However, in the suggested approach, T2FLCs are online updated based on the learning laws that are extracted from I&I theorem, and there is no need to any iterations. In other words, at each sample time, both rules and FS parameters are updated at once. At each sample time, the parameters of rules and FSs are obtained by taking the integral form adaptation rules (93-94). Then, there is no huge computations and its implementation is quite feasible.

VII. CONCLUSION

In this paper a new strategy is developed based on I&I approach for voltage regulation in PV/FC/Battery systems. Some tuning rules are presented for uncertain parameters such that the I&I stabilization criterions are satisfied. The perturbations are compensated by the a suggested deep learning T2FLC. In three faulty conditions the performance is evaluated. For first one, irradiation is suddenly changed from its
nominal level, it is shown the PV power well tracks its optimal target, and the output voltage is also well regulated on its reference set point. For the second examination, the effect of variation of temperature is taken to account, and temperature is considered to be time-varying. The simulations show a good resistance against temperature disturbance. Finally, for the last examination, beside variation of temperature and irradiation, the output load is also considered to be time-varying. Simulation results and comparison with other new controllers demonstrates that the suggested control scenario results in better regulation proficiency under uncertain dynamics and difficult faulty conditions.

APPENDIX
PARAMETERS DESCRIPTIONS

| TABLE 3. Parameter definition, see equation (1). |
|-----------------------------------------------|
| Parameter | Definition | Unit |
| R | Gas constant | J/mol K |
| ξH2O | Water partial pressures | atm |
| T | Stack temperature | kelvin |
| E0 | Voltage for reaction free energy | volts |
| I | Internal resistance | ohms |
| IC | Current | A |
| ξH2 | Hydrogen partial pressure | atm |
| N0 | Number of cells | - |
| ξO2 | Oxygen partial pressure | atm |
| F | Faraday’s constant | C/mol |

| TABLE 4. Parameter definition, see equations (2-6). |
|-----------------------------------------------|
| Parameter | Definition | Unit |
| kH2 | Index of Hydrogen | kmol/s·atm |
| nH2 | Hydrogen time constant | sec |
| kH2O | Index of Water | kmol/s·atm |
| nH2O | Water time constant | sec |
| rH2O | Ratio of hydrogen to oxygen | - |
| QH2 | Hydrogen flow rate | mol/s |
| τc | Constant | kmol/s · A |
| QO2 | Oxygen flow rate | mol/s |
| Uopt | Employment | - |
| κf | Fuel time constant | sec |

| TABLE 5. PV parameter definition, see equation (8). |
|-----------------------------------------------|
| Parameter | Description |
| n | Number of cells |
| G (w/m²) | Solar radiation |
| Q | Electron charge |
| Eγ (ev) | Energy of Band-Gap |
| T (°c) | Temperature of PV |
| k_b (J/τ) | Boltzmann’s constant |
| R_i and R_s (Ω) | Equivalent resistances |
| A | Diode ideality constant |
| i_s (A) | Saturation current |
| T_i (°c) | Target temperature |
| t_ph (A) | Photo generated currents |

| TABLE 6. Battery parameters definition, see equation (11). |
|-----------------------------------------------|
| Parameter | Definition |
| t_ph (Ω) | Internal resistance |
| V_boc (v) | Open circuit voltage |
| E_Loss (w) | Power losses |
| E_max (J) | Maximum chargeable energy |
| β1 and β2 | Charge/Discharge rates |

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