New fuzzy control design for photovoltaic system using LMI technique

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Abstract. The T-S Fuzzy model-based technique (T-S: Takagi-Sugeno) is used in this research to offer a new fuzzy state feedback control for solar systems with output charge. We discuss a DC-DC boost converter to manage the output power of a solar panel array under shifting meteorological circumstances. To reach optimal power point, a T-S reference model is employed to create a fuzzy state feedback control that must be tracked. Solving a series of linear matrix inequalities (LMIs) yields controller gains. Furthermore, the proposed solution reduces the oscillation disadvantage near the highest power point while simultaneously shortening the tracking time. Finally, simulation of the solar system employing the proposed state feedback control shows that the proposed approach is effective even in the face of climate change.

1 Introduction

Energy is critical to our way of life and economy. The industrial revolution increased energy demand significantly. Fossil fuels are gradually depleting. The long-term viability of our civilization is jeopardized. Greenhouse gas emissions from conventional energy generation, on the other hand, continue to rise. Global challenges include reduced carbon dioxide emissions, secure, clean, and affordable energy, and more sustainable energy systems [1]. Renewable energy sources are regarded as an excellent source of clean and sustainable energy.

Solar energy, wind energy, and other renewable energy sources... Photovoltaic (PV) systems, which appear to be one of the most promising renewable energy sources, have drawn the attention of researchers. Solar energy is environmentally friendly, low-maintenance, and low-noise [1,2].

However, two major factors limit photovoltaic system adoption. These are high installation costs and inefficient energy conversion [2]. One of the effective methods for lowering photovoltaic power system costs and increasing solar energy utilization efficiency is the high power point tracking system (MPPT) of photovoltaic modules [3]. The (MPPT) system extracts the maximum power from a Photovoltaic module, delivers it to the load, and increases efficiency [4].

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To increase the solar modules' output power, various techniques have been developed, including the perturb and observe (P&O) method [5, 6, 7, 8], incremental conductance (INC) methods [5, 9, 10, 11], maximum power point (MPP) estimation [5, 12], and artificial intelligence methods [13, 14, 15, 16, 17]. Vahid et al. (2018) suggested a strong feedback system linearization controller for MPPT in PV systems using a modified INC method, ensuring overall closed-circuit internal stability. Nonetheless, the system only takes a reasonable amount of time for getting to the MPP. Nabulsi and Dhaouadi (2012) proposed a new Perturb and Observe scheme utilizing fuzzy logic controller (FLC) in which the PV reference voltage is self-adjusted with variable step size to achieve the MPP accurately. Furthermore, the INC method, like the P&O method, is influenced by the same factors, necessitating a trade-off between tracking speed and oscillations to achieve an MPP. Masoum et al. (2002) proposed open-circuit voltage and short-circuit current (SCC) algorithms that, due to the approximation used in these algorithms, are unable to find the true MPP. Priyabrata Shaw and Priyabrat Garanayak (2019) provide a fast, reliable MPPT approach based on analog circuitry that enhances tracking capability by using a boost DC-DC converter.

Because they're straightforward affordability, and usefulness, the Perturb & Observe and Increment Condition methods are frequently utilized in industrial PV panels. However, a PV system with a DC/DC boost converter is treated as a linear system in these conventional controls, leading to subpar dynamic performance and significant oscillations around the MPP. Furthermore, during rapid changes in atmospheric conditions, the external disturbance is ignored, resulting in slow and incorrect tracking. On the other hand, the problem of asymmetric saturation of duty ratio (limited between 0 and 1) is not addressed in these traditional approaches, which is a source of performance degradation. Indeed, actuator saturation can degrade the performance of system with a closed-loop and, in some cases, a steady closed-loop system to become unstable [18, 19].

Many T-S fuzzy models are used in fuzzy MPPT controllers have been proposed recently. The latter model's basic concept is to group linear models to describe processes. As a result, linear control theory is widely applied to nonlinear systems by utilizing the principle of Parallel Distributed Compensation (PDC) [20]. The stability criteria of the augmented T-S fuzzy system, which are easily converted into linear matrix inequalities (LMIs), are used to calculate the fuzzy controller gains and efficiently solved using convex programming techniques [21].

This work proposes a novel MPPT controller based on the TS fuzzy model that can effectively eliminate the oscillation of the PV system in various steady states, thereby reducing overshoot and accelerating the time response. As a summary of the suggested fuzzy control strategy: First, a fuzzy TS controller is created using a nonlinear model of the photovoltaic system. The optimal photovoltaic voltage is then used to generate an optimal reference model, which is generated using an algorithm for the adaptive neuro-fuzzy inference system (ANFIS) with inputs of cell temperature and solar irradiation. The best reference model and the planned T-S fuzzy controller are then combined to generate a non-linear tracking controller. The Lyapunov method is used to analyze and describe the augmented system's stability.

2 T–S fuzzy model representation of PV system

2.1 Boost converter model

As seen in Figure 1, the following equations describe the DC-DC boost converter's dynamic model:
An important point to remember is that the diode's forward voltage \( v_d \) and the internal resistance \( R_m \) have been taken into account in this work, which can affect the PV system's regulation.

The PV system can be described using the previous equations and a new state variable \( \dot{x} = f(x(t)) + Bu(t) + \eta(t), u(t) \in [0, 1], \) (2)

Where

\[
\dot{x} = \begin{bmatrix}
-\frac{R_L}{L} i_L + \frac{1}{L} V_{PV} + \frac{v_0 + v_d - R_m i_L}{L} u_{PV} \\
-\frac{1}{C_1} i_L \\
0
\end{bmatrix},
\begin{bmatrix}
i_L \\
V_{PV} \\
u_{PV}
\end{bmatrix},
B = \begin{bmatrix}
0 \\
0 \\
1
\end{bmatrix},
\eta = \begin{bmatrix}
-\frac{v_0 + v_d}{L} \\
-\frac{1}{C_1} i_{PV} \\
0
\end{bmatrix}
\]

### Table 1. Photovoltaic conversion system parameters.

<table>
<thead>
<tr>
<th>System Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boltzmann’s constant, ( k )</td>
<td>( 1.38 , e^{23} , J/K )</td>
</tr>
<tr>
<td>Ideal factor of photovoltaic cell, ( A )</td>
<td>( 1.1 , V )</td>
</tr>
<tr>
<td>Shunt resistance, ( R_{sh} )</td>
<td>( 360 , \Omega )</td>
</tr>
<tr>
<td>Series resistance, ( R_s )</td>
<td>( 0.18 , \Omega )</td>
</tr>
<tr>
<td>Number of cells connected in series, ( n_s )</td>
<td>( 36 )</td>
</tr>
<tr>
<td>Number of modules in parallel, ( n_p )</td>
<td>( 1 )</td>
</tr>
<tr>
<td>Temperature reference, ( T_0 )</td>
<td>( 298.15 , K )</td>
</tr>
<tr>
<td>Irradiation reference, ( G_0 )</td>
<td>( 1000 , W/m^2 )</td>
</tr>
<tr>
<td>Open-circuit voltage, ( V_{oc} )</td>
<td>( 21.6 , V )</td>
</tr>
<tr>
<td>Nominals short-circuit current, ( I_{scn} )</td>
<td>( 3.8 , A )</td>
</tr>
<tr>
<td>Nominal PV voltage, ( V_{pm} )</td>
<td>( 21 , V )</td>
</tr>
<tr>
<td>Load resistance, ( R )</td>
<td>( 35 , \Omega )</td>
</tr>
<tr>
<td>Output capacitor, ( C_2 )</td>
<td>( 4 , e^{-6} , F )</td>
</tr>
<tr>
<td>Input capacitor, ( C_1 )</td>
<td>( 1 , e^{-3} , F )</td>
</tr>
<tr>
<td>Inductor, ( L )</td>
<td>( 4 , e^{-2} , H )</td>
</tr>
<tr>
<td>Resistance of self-inductance, ( R_L )</td>
<td>( 0.5 , \Omega )</td>
</tr>
<tr>
<td>Resistance of IGBT characterizing, ( R_m )</td>
<td>( 5 , e^{-2} , \Omega )</td>
</tr>
<tr>
<td>Diode’s forward voltage, ( v_d )</td>
<td>( 1.9 , V )</td>
</tr>
</tbody>
</table>
Table 2. Photovoltaic system parameters.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Significations</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{PV}$</td>
<td>PV output voltage</td>
</tr>
<tr>
<td>$I_{PV}$</td>
<td>PV output current</td>
</tr>
<tr>
<td>$u$</td>
<td>Control input corresponding to the duty cycle</td>
</tr>
<tr>
<td>$i_L$</td>
<td>Boost self-inductance current</td>
</tr>
<tr>
<td>$V_o$</td>
<td>Output load voltage</td>
</tr>
<tr>
<td>$i_o$</td>
<td>Output load current</td>
</tr>
</tbody>
</table>

The photovoltaic system under consideration, as shown in Figure 1, consists of a DC load, a DC / DC boost transformer and a PV panel. The following photovoltaic system parameters (table 2) will be used in this study:

Figure 1 depicts a global control structure scheme for achieving the MPP under various climatic conditions.

In order to generate the best PV current $I_{PV, opt}$, the two quantities T and G are sent to the MPP searching algorithm.

In order to provide the desired trajectory $x(t)$ for $x_r(t)$ tracking, this latter is taken into consideration as an input control signal for the T-S fuzzy reference model. To achieve the best power tracking, a T-S fuzzy controller is integrated into the MPPT structure to force the load power to follow the optimal power $P_{opt}$.

2.1 T.S Fuzzy system of the Photovoltaic System

The Photovoltaic nonlinear model is transformed into a T.S fuzzy model to create the fuzzy controller, with $i_L$ and $V_o$ serving as decision variables [22]. As a result, the nonlinear state space form is as follows:

$$\dot{x}(t) = A(i_L, V_o)x(t) + Bu(t) + \eta(t)$$ (3)

Where

$$A(i_L, V_o) = \begin{bmatrix} -\frac{R_L}{L} & 1 & \frac{V_o + v_d - R_m i_L}{L} \\ 1 & 0 & 0 \\ -\frac{1}{C_1} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$
\[ B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \quad \eta = \begin{bmatrix} -\frac{v_o + v_d}{L} \\ \frac{1}{C_1} I_{PV} \\ 0 \end{bmatrix} \]

Assume that:

\[ i_{l_{\min}} \leq i_l \leq i_{l_{\max}}, \quad V_{0_{\min}} \leq V_0 \leq V_{0_{\max}} \quad (4) \]

The nonlinear system (3) can be described by a T-S model with \( r = 2^n = 2^2 \) fuzzy (if-then) rules using sector nonlinearity transformation [23]:

\[ \text{Rule } i: \text{ If } z_1(t) \text{ is } F_{1i} \text{ and } z_2(t) \text{ is } F_{2i} \text{ then} \]

\[ \dot{x}(t) = A_i x(t) + B_i u(t) + \eta(t), \quad i = 1, \ldots, 4 \]

where \( z_1 = i_l \) and \( z_2 = V_0 \) are the premise variables, \( F_{11}, F_{12}, F_{21} \) and \( F_{22} \) are the membership functions given by:

\[
\begin{align*}
F_{11}(i_l) &= \frac{i_{l_{\max}} - i_{l_{\min}}}{i_{l_{\max}} - i_{l_{\min}}}, \quad F_{12}(i_l) = 1 - F_{11}(i_l) \\
F_{21}(V_0) &= \frac{V_0 - V_{0_{\min}}}{V_{0_{\max}} - V_{0_{\min}}}, \quad F_{22}(V_0) = 1 - F_{21}(V_0)
\end{align*}
\]

The local model matrices are defined as follows:

\[
A_1 = \begin{bmatrix}
-\frac{R_l}{L} & 1 & V_{0_{\max}} + v_d - R_m i_{l_{\max}} \\
-\frac{1}{C_1} & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}, \quad A_2 = \begin{bmatrix}
-\frac{R_l}{L} & 1 & V_{0_{\min}} + v_d - R_m i_{l_{\max}} \\
-\frac{1}{C_1} & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}, \\
A_3 = \begin{bmatrix}
-\frac{R_l}{L} & 1 & V_{0_{\max}} + v_d - R_m i_{l_{\min}} \\
-\frac{1}{C_1} & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}, \quad A_4 = \begin{bmatrix}
-\frac{R_l}{L} & 1 & V_{0_{\min}} + v_d - R_m i_{l_{\min}} \\
-\frac{1}{C_1} & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

\[ B_1 = B_2 = B_3 = B_4 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}. \]

The fuzzy rule-based system's overall output is provided by the product-inference rule, singleton fuzzifier, and center of gravity defuzzifier.

\[ \dot{x}(t) = \sum_{i=1}^{r} h_i(z(t)) (A_i x(t) + B_i u(t)) + \eta(t) \quad (6) \]

Where \( h_i(z) = \omega_i(z)/\sum_{i=1}^{r} \omega_i(z), \quad \omega_i(z) = \prod_{j=1}^{n} F_{ij}(z_j) \)

For all \( t > 0, h_i(z) \geq 0 \) and \( \sum_{i=1}^{r} h_i(z) = 1 \)

The following lemma [24] is required to facilitate the design of a fuzzy controller.

**Lemma 1**: If the following conditions hold:

\[ M_{ii} < 0 \quad \text{with} \quad i = 1, 2, \ldots, r \]

\[ \frac{1}{r-1} M_{ii} + M_{ij} + M_{ji} < 0 \quad \text{with} \quad i \neq j; \quad i, j = 1, 2 \ldots r \]

The following inequality holds true:
\[ \sum_{i=1}^{r} \sum_{j=1}^{r} h_i(z(t)) h_j(z(t)) M_{ij} < 0 \]

### 3 T-S fuzzy state feedback control analysis and synthesis

The goal is to create a T-S Fuzzy state feedback control capable of driving the Photovoltaic system's state \(x(t)\) to track an optimal reference model \(x_r(t)\).

\[ x(t) - x_r(t) \rightarrow 0 \text{ as } t \text{ tends towards infinity} \]

The error tracking system can be rewritten as follows:

\[ \dot{e}(t) = \sum_{i=1}^{r} h_i(z(t))(A_i e(t) + B_i u(t)) \] \hspace{1cm} (8)

Where, \(A_i\) and \(B_i\) are appropriate subsystem matrices, and \(e(t) = x(t) - x_r(t)\) is the state of the tracking error system.

The tracking control problem is addressed by the state feedback controllers \(u(t)\) as follows:

Rule \(i\): if \(z_1(t)\) is \(F_{1i}\) and \(z_2(t)\) is \(F_{2i}\) then

\[ u(t) = -K_i e(t) \]

The final output of the fuzzy controller is given by the following form:

\[ u(t) = -\sum_{i=1}^{r} h_i(z(t)) K_i e(t) \] \hspace{1cm} (9)

Applying control law to the error system, the closed loop system takes the following form:

\[ \dot{e}(t) = \sum_{i=1}^{r} \sum_{j=1}^{r} h_i(z(t)) h_j(z(t)) \left( A_i e(t) - B_i K_j e(t) \right) \]

\[ \dot{e}(t) = \sum_{i=1}^{r} \sum_{j=1}^{r} h_i(z(t)) h_j(z(t)) \left( A_i - B_i K_j \right) e(t) \]

\[ \dot{e}(t) = \sum_{i=1}^{r} \sum_{j=1}^{r} h_i(z(t)) h_j(z(t)) A_{ij} e(t) \]

Where \(A_{ij} = (A_i - B_i K_j)\) \hspace{1cm} (10)

**Theorem 1:** If a symmetric positive definite matrix \(P\) and matrices \(G\) and \(R_j (\text{with } j = 1, 2, 3, 4)\) exist, the closed loop system (9) is asymptotically stable, and the following LMIs can be solved:

\[ M_{ii} < 0 \quad \text{with} \quad 1 \leq i \leq 4 \] \hspace{1cm} (11)

\[ \left( \frac{2}{3} M_{ii} + M_{ij} + M_{ji} \right) < 0 \quad \text{with} \quad 1 \leq i < j \leq 4 \] \hspace{1cm} (12)

Where

\[ M_{ij} = \begin{bmatrix} A_i G & \left( G^T A_i^T - B_i R_j - R_j^T B_i^T \right)^T \ P + A_i G - B_i R_j - G^T \\ * & -G - G^T \end{bmatrix} \] \hspace{1cm} (13)

The control law is given by:

\[ K_j = R_j G^{-1} \]
Proof. According to Theorem 1 of [25], the dynamics of the system (9) are asymptotically stable if and only if the following conditions are met:

\[ \begin{bmatrix} AX_1 + X_1^T A^T & P + AX_2 - X_1^T \\ 0 & -X_2 - X_2^T \end{bmatrix} < 0 \]  \hspace{1cm} (14)

We replace \( A \) with \( \sum_{i=1}^{r} \sum_{j=1}^{r} h_i(z(t)) h_j(z(t)) A_{ij} \) and \( X_1, X_2 \) with \( G \) in condition (14), as a result, we apply Lemma 1 and we obtain the conditions (11), (12) and (13) where \( G \) is a free nonsingular matrix.

\[ K_j G = R_j. \]  \hspace{1cm} This completes the proof.

4 Simulation results

To validate the effectiveness and validity of the proposed method, simulation tests were performed on a solar power generation system (3) using the parameters listed in Table 1 with \( |V_0| \leq 17.1 \) and \( |i_L| \leq 3.5 \).

Solving the LMIs in theorem1 with the MATLAB LMI TOOLBOX yields the T-S fuzzy controller gains.

We have:

\[
\begin{align*}
K_1 &= \begin{bmatrix} 0.5354 & 0.0563 & 310.7546 \\
K_2 &= \begin{bmatrix} 0.5429 & 0.0569 & 310.8556 \\
K_3 &= \begin{bmatrix} 0.5016 & 0.0593 & 311.1229 \\
K_4 &= \begin{bmatrix} 0.4951 & 0.0583 & 310.2274 \\
\end{align*}
\end{align*}
\]

In open loop, we observe in figures 3, 4, 5 and 6 that the state of the PV system \( x(t) = (i_L \ V_{pv} \ u_{pv})^T \) moves away from the reference state and does not follow the optimal reference model \( x_{r}(t) = (i_{Lopt} \ V_{pv_{opt}} \ u_{pv_{opt}})^T \). Whereas in closed loop, figures 1 and 2 show that the fuzzy controller capable of driving the state of the PV system \( x(t) \) to track an optimal reference model \( x_{opt}(t) \). Then, the feedback tracking control is required to satisfy:

\[ e(t) = x(t) - x_{r}(t) \rightarrow 0 \text{ as } t \text{ increase.} \]

With:

\[
\begin{align*}
\begin{cases}
e_1(t) = x_1(t) - x_{r1}(t) \\
e_2(t) = x_2(t) - x_{r2}(t) \\
e_3(t) = x_3(t) - x_{r3}(t) \\
\end{cases}
\end{align*}
\]

For the different fuzzy controller gains \( K_i (i = 1, ..., 4) \)

Fig. 2. Fuzzy control strategy for MPPT
Conclusion

This paper proposes an efficient TS fuzzy controller for MPP tracking in PV conversion systems. Solving a set of LMI criteria results in a stable controller capable of tracking the global maximum power point. In steady state, the proposed controller can guide the photovoltaic system to track the optimal reference model with high tracking accuracy and minimal oscillation.

References


