Roach Infestation Optimization MPPT Algorithm for Solar Photovoltaic System

Chittaranjan Pradhan¹,∗, Nicholas Kakra Ntiakoh¹ and Rajnish Kaur Calay²

¹ Arctic Centre for Sustainable Energy, Department of Electrical Engineering, The University of Tromsø -UiT Arctic University of Norway, Narvik Campus, Norway-8514; chittaranjan.pradhan@uit.no; nicholas.kakra@gmail.com
² Department of Building, Energy and Material Technology, UiT The Arctic University of Norway, Narvik Campus, Norway-8514; rajnish.k.calay@uit.no
∗ Correspondence: chittaranjan.pradhan@uit.no

Abstract: Of all the renewable energy sources, solar photovoltaic (PV) power is estimated to be a popular source due to several advantages such as its free availability, absence of rotating parts, integration to building such as rooftops and less maintenance cost. The nonlinear current–voltage (I–V) characteristics and power generated from a PV array primarily depend on solar insolation/irradiation and panel temperature. The extracted PV output power is influenced by the accuracy with which the nonlinear power–voltage (P–V) characteristic curve is traced by the maximum power point tracking (MPPT) controller. In this paper, a bio-inspired roach infestation optimization (RIO) algorithm is proposed to extract the maximum power from the PV system (PVS). To validate the usefulness of the RIO MPPT algorithm, MATLAB/Simulink simulations are performed under varying environmental conditions, for example, step changes in solar irradiance, and partial shading of the PV array. Furthermore, the search performance of the RIO algorithm is examined on different unconstrained benchmark functions, and it is that realized that the RIO algorithm has improved convergence characteristics in terms of finding the optimal solution than Particle swarm optimization (PSO). The results demonstrated that the RIO-based MPPT performs remarkably in tracking with high accuracy as the PSO-based MPPT.

Keywords: DC-DC Boost converter; Maximum power point tracking (MPPT); Partial shading condition (PSC); Particle swarm optimization (PSO); Roach infestation optimization (RIO); Solar photovoltaic system.

1. Introduction

The use of non-renewable energy sources such as oil, coal, and natural gas for the production of electricity produces harmful emissions that affect the environment and cause global warming. The urgent necessity to protect this planet has called for cleaner sources of energy, of which solar power plays a significant role. Solar is a pollution-free source of energy, and it is abundantly available. The global growth of solar PV capacity has been increased consistently since 2000. Between 2000 and 2019, numbers grew by 632.4 gigawatts. In 2019, solar PV capacity reached 633.7 gigawatts globally, with 116.9 gigawatts installed that year [1]. Figure 1 illustrates the aggregated solar PV capacity in gigawatts by select countries as of 2019.

Photovoltaics (PVs) is converting light (from the sun) into electricity by the use of semiconductor materials that shows the photovoltaic effect. A PV system utilizes solar modules, which comprise several solar cells, generating electrical energy or power [2-4]. Despite the recent technological enhancement in PV operational characteristics, such as reducing costs and improving efficiency, the lower energy conversion efficiency of PV systems (PVs) remains a significant drawback to the utilization of PV power. One other major issue with PV power generation is the reliance on environmental influences, such
as solar irradiance and ambient temperature [5-7]. Since the cost involved in PV power generation is high and to make more profit on investment, it is very essential to extract most of the available solar energy through the panels. Therefore, the control unit of the PV system must be compelled through an efficient MPPT method for harvesting the maximum power from the installed PV arrays by generating an appropriate duty ratio to regulate the DC-DC converter embedded in the system [8-10]. In [9], a comprehensive review of the DC–DC converter topologies and their modulation strategies for solar PV systems. Taking into account all affecting factors of the PV, boosting the MPPT efficacy using a low-cost hardware approach is essential to improving the operation of the PVS [11-13].

Figure 1. Global cumulative solar PV capacity in 2019 [1]

The objective of an efficient MPPT controller is to meet the ensuing characteristics such as accuracy, robustness, and faster-tracking speed under partial shading conditions (PSCs) and climatic variations such as a change in solar irradiation and temperature. To realize these objectives, numerous traditional techniques in artificial intelligence and bio-inspired approaches/algorithms have been recommended in the previous literature [13-16]. The most common conventional MPPT methods are the incremental conductance (IC) [17], perturb and observe (P&O) [18], and hill-climbing (HC) [19]. These conventional methods are simple, easy implementation, and can track the MPP effectively under normal environmental circumstances. However, they have a disadvantage as continuous oscillations follow around the MPP, causing significant power loss in the steady-state condition. In this perspective, various artificial intelligent MPPT methodologies have been implemented to handle the shortcomings of the conventional MPPT methods, especially highly intermittent conditions. These include fuzzy logic control (FLC) [20], artificial neural network (ANN) [21], firefly algorithm (FA) [22], PSO [23], ant colony optimization (ACO) [24], flower pollination algorithm (FPA) [25], invasive weed optimization [26], salp swarm optimization [27], bat optimization [28], Neighboring-Pixel-based virtual imaging technique [29], surface-based polynomial fitting [30], Jaya algorithm [31], most valuable player algorithm [32] and many more. The results demonstrated that the artificial intelligence algorithms have high accuracy and stability in tracking the global MPP in different environmental conditions.

In practice, each intelligent technique can only be employed in its best performance in a desirable scenario and is generally not fitting for a wide range of applications [16, 33]. From this perspective, applying or designing a new intelligent algorithm has been always welcome, for improving the search performance [33-34]. By Seeing the efficacy of the soft-computing based intelligent optimization algorithms, in this paper, a bio-inspired Roach
Infestation Optimization (RIO) for obtaining the maximum power from the PV is projected.

The main contributions of this work can be summarized as follows:

• The paper presents the RIO algorithm to track the GMPP of the PV system.
• The efficacy of the proposed RIO algorithm has been tested in different unconstrained benchmark functions and as well as MPPT of the PV system for both symmetrical irradiation and PSCs.
• The proposed population-based RIO technique achieves excellence-searching performance in terms of convergence time and accuracy as compared to PSO.

The paper is organized as follows. Section 2 addresses the studied PV system. In Section 3, an overview of the RIO algorithm is explained. The Simulation results and discussions are provided in Section 4. Finally, the conclusion and future work is illustrated in Section 5.

2. Studied Photovoltaic (PV) System

To establish the behavior of a solar cell electronically, an equivalent model is made based on basic electrical components. The solar cell is modeled by a current source in parallel with a diode, a shunt resistance and a series resistance component as presented in Figure 2 [7]. The detailed mathematical modeling of the PV cell is taken from [26].

In Figure 2, $R_s$ and $R_{sh}$ are the intrinsic series and shunt resistor of the PV cell (Ω), respectively. $I_{ph}$ is the current through $Rs$. $D_i$ is the intrinsic diode. $I_d$ is diode current (A), $I_{sh}$ is shunt current (A), $I_{ph}$ is the light-generated current in the cell (A). $V_{pv}$ and $I_{pv}$ are the PV output voltage (V) and current (A), respectively. $G$ is the solar irradiation (W/m²).

In Figure 2, the current generated by the solar cell is equivalent to that produced by the current source minus that which flows through the diode and the shunt resistor which is established by Kirchhoff’s current law as follows [19]:

$$I_{pv} = I_{ph} - I_d - I_{sh}$$

(1)

The current through these elements can be given by the voltages across them:

$$V_d = V_{pv} + R_s I_{pv}$$

(2)

Where, $V_d$ is the voltage across the diode (V).

The PV cell is quantified by current-voltage characteristic operation as follows [19]:

$$I_{pv} = I_{ph} - I_d - I_{sh}$$

(1)
\[ I_{pv} = n_p I_{ph} - n_p I_p \left( \exp \left( \frac{q(V_{pv} + I_{pv} R_s)}{AKT_s} - 1 \right) \right) \left( \frac{V_{pv} + I_{pv} R_s}{R_{sh}} \right) \]

with

\[ I_p = I_s \left( \frac{T}{T_r} \right)^{3/4} \exp \left( \frac{qV_{oc}}{AK} \left[ \frac{1}{T_r} - \frac{1}{T} \right] \right), \quad I_{ph} = I_c + [K(T_0 - T)] \frac{G}{1000} \]

where, \( n \) and \( n_p \) are the number of cells connected in series and parallel, \( q \) is the electron charge (C), \( K \) is Boltzmann’s constant (J/K), \( A \) is the p-n junction’s idealistic factor, \( T \) is the cell’s absolute temperature (°K), \( T_r \) is the cell reference temperature (°K), \( I_{ph} \) is the cell’s photocurrent (it depends on the solar irradiance and temperature), \( I_s \) is the cell’s reverse saturation current, \( I_c \) is the short-circuit current of the PV cell, \( V_{oc} \) is the open-circuit voltage of the PV cell and \( G \) is the solar irradiance.

The studied PV system (PVS) consists of four-series (4S) connected PV modules, a resistive load, and a non-isolated DC-DC boost converter with the MPPT technique. The DC-DC converter acts as an interface between the PV panel and the load, allowing the follow-up of the maximum power. The MATLAB/Simulink model of the studied PVS is shown in Figure 3. The modeling parameters of the PVS and DC-DC converter are given in Tables 1 and 2, respectively. The detailed modeling and selection of the DC-DC boost converter components/parameters are taken from [36-37].

**Table 1. Studied PV system parameters**

| System parameters/data | Symbol  | Value       |
|------------------------|---------|-------------|
| For one PV module      |         |             |
| Maximum power for 1000 W/m² and 25°C | \( P_{max}^{PV} \) | 59.85W |
| Voltage at MPP for 1000 W/m² and 25°C | \( V_{max}^{PV} \) | 17.1V |
| Current at MPP for 1000 W/m² and 25°C | \( I_{max}^{PV} \) | 3.5A |
| Open-circuit voltage   | \( V_{oc} \) | 21.1V |
| Short-circuit current  | \( I_c \) | 3.8A |
| Series resistance      | \( R_s \) | 0.10363 Ω |
| Shunt resistance       | \( R_{sh} \) | 283.3724 Ω |
| Ideality factor        | \( A_0 \) | 1.5406 |
| Temperature co-efficient of \( I_{sc} \) |                  | 0.00247 %/°C |
| Temperature co-efficient of \( V_{oc} \) |                  | -0.8 %/°C |

**Table 2. DC-DC boost converter parameters**

| System parameters/data | Symbol | Value |
|------------------------|--------|-------|
| Capacitor              | \( C \) | 464μF |
| Input filter capacitor | \( C_i \) | 10μF |
| Inductor               | \( L \) | 1.14mH |
| Switching frequency    | \( f_s \) | 50kHz |
| Load resistance        | \( R \) | 53 Ω |
In Figure 3, \( R \) is the load resistance. \( L \) and \( C \) are the boost converter inductor and capacitor, respectively. \( S_w \) is the power electronics switch (e.g., MOSFET). \( D_1 \) is the free-wheeling diode, \( C_1 \) is the input filter capacitor and \( D \) is the duty ratio.

### 3. Roach Infestation Optimization (RIO) Based MPPT Algorithm

The RIO was originally introduced by Haven et al., as a cockroach-inspired algorithm [38]. The RIO was adapted from the traditional PSO algorithm, and therefore it has some parameters similar to the PSO. It is studied that cockroaches dislike the light and like the gathering [38]. Whenever a cockroach encounters another neighboring cockroach, it stops and socializes. During this period, information about the darkest known location is shared. When a cockroach is hungry it leaves friends and comfortable shelter and searches for food. The equation that models to find the Darkness behavior of a cockroach is evaluated as follows [38]:

\[
v_i^{l+1} = C_0 v_i^l + C_{\text{max}} R_i \cdot (p_{i}^{\text{best}} - x_i^l)
\]

where, \( v_i^l \) represents the velocity of \( i^{th} \) particle/agent (i.e., cockroach) for the \( l^{th} \) iteration, \( x_i^l \) is the current location for the \( l^{th} \) iteration, \( p_{i}^{\text{best}} \) is the best dark place (location) of the \( i^{th} \) agent, \( C_0 \) and \( C_{\text{max}} \) are constants and \( R_i \) is a random number.

If a cockroach comes within a detection radius of another cockroach, they stop, and these cockroaches will group and share information by adapting the darkest local place \( L_i^{\text{best}} \) in the search space.

\[
L_i^{\text{best}} = \arg \min \{ \text{Function}(p_k) \}, k = \{ i, j \}
\]

where, \( (i, j) \) are the represents of the two socializing cockroaches and \( p_k \) is the darkest recognized place for the individual cockroach. Now, (4) can be presented as follows:

\[
v_i^{l+1} = c_0 v_i^l + c_{\text{max}} R_i \cdot (p_{i}^{\text{best}} - x_i^l) + c_{\text{max}}^2 R_i \cdot (L_i^{\text{best}} - x_i^l)
\]
It is noticeable that (6) is very much similar to the PSO velocity update. While the global best is substituted by a group best $L_{i}^{best}$ in RIO.

**Table 3. Parameters for RIO [38] and PSO [39] algorithms**

| Optimization algorithm | parameter | Symbols | value |
|------------------------|-----------|---------|-------|
| RIO*                   | Cockroach parameter | $C_0$ | 0.4 |
|                        | Cockroach parameter | $C_{max}$ | 1.4 |
| PSO                    | Cognitive parameter | $c_1$ | 1.2 |
|                        | Social parameter | $c_2$ | 1.6 |
|                        | Weight parameter | $w$ | 0.4 |

**Figure 4. Flowchart of proposed RIO algorithm for MPPT**
The flowchart of the RIO for MPPT is presented in Figure 4. To obtain the results, the value of the algorithm-specified control parameters of the PSO and RIO algorithms is given in Table 3. The DC-DC boost converter receives the PV voltage ($V_{pv}$) and current ($I_{pv}$) from the PVS and subsequently regulates it by adjusting the duty ratio ($D$). The value of $D$ is updated using the optimization algorithms to achieve the MPP as shown in Figure 3.

In this work, the global peak power ($G_P$) of the PV system is attained using the optimization algorithm to update $D$ in the search process during both uniform irradiation/temperature and PSCs.

4. Results and Discussions

A MATLAB/Simulink (R2020b) software is employed for modeling and to justify the effectiveness of the RIO-based MPPT method of the PV system (Figure 3). Different case studies have been realized to show the efficacy of the RIO algorithm than PSO for getting the optimal solution of different unconstrained benchmark functions and GMPP of the PV system. The time-domain simulations have been accomplished for both uniform irradiation and PSCs such as (i). Uniform solar irradiance (Patterns-1, 2 and 5) and (ii). PSCs (Patterns-3, 4 and 6) as shown in Figure 5. Table 4 illustrates the combination of various patterns selected for the PVS to plot the graphs. In the case of uniform/symmetrical solar irradiance, both solar irradiance and temperature remain constant, whereas, for PSCs, different values of solar irradiation ($G$) are considered, for the PV modules. The PVS is simulated under the various scenarios and the simulation results are demonstrated which are discussed below:

Table 4. Shading patterns of PVS for different solar irradiation ($G$)

| Shading pattern | Module-1 | Module-2 | Module-3 | Module-4 |
|-----------------|----------|----------|----------|----------|
| Pattern-1 at 25°C Symmetrical shading | 10000 | 1000 | 1000 | 1000 |
| Pattern-2 at 25°C Symmetrical shading | 600 | 600 | 600 | 600 |
| Pattern-3 at 25°C Partial shading | 1000 | 800 | 600 | 400 |
| Pattern-4 at 25°C Partial shading | 800 | 600 | 400 | 200 |
| Pattern-5 at 20°C Symmetrical shading | 1000 | 1000 | 1000 | 1000 |
| Pattern-6 at 20°C Partial shading | 800 | 600 | 400 | 200 |

Figure 5. 4S structure of PV array system (a). Pattern-1, (b). Pattern-2, (c). Pattern-3, (d). Pattern-4
3.1. P-V and I-V characteristics curves of the PV system

The performance of a solar panel affects both uniform irradiation/temperature and PSCs. The PV system, whether a module, string, or array exhibits a P-V curve exhibiting multiple peaks, a Global Maximum Power Point (GMPP) which is the highest peak and Local Maximum PowerPoints (LMPPs) are the other multiple peaks. The P-V and I-V graphs under each pattern are given in Figures 6 and 7, respectively. From the figures, it can be noticed that the higher the solar irradiation, the peak PV will be higher and vice-versa. The same can be observed for other combinations of solar irradiation and temperature. The exact value of the global peak power \(G_P\), the corresponding voltage \(V_{mpp}\), and current \(I_{mpp}\) at MPP of the PVS under the selected test patterns are given in Table 5.

![Figure 6. P-V graph for different shading patterns](image)

![Figure 7. I-V graph for different shading patterns](image)
Table 5. Global peak power ($G_p$) for different patterns

| Patterns | $G_p$ (W) | $V_{mpp}$ (V) | $I_{mpp}$ (A) |
|----------|-----------|---------------|---------------|
| Pattern-1 | 237.964   | 68.4002       | 3.47899       |
| Pattern-2 | 137.919   | 66.455        | 2.07537       |
| Pattern-3 | 115.856   | 52.6927       | 2.19871       |
| Pattern-4 | 76.5723   | 52.3029       | 1.46402       |
| Pattern-5 | 250.314   | 71.7273       | 3.4898        |
| Pattern-6 | 80.4385   | 54.8416       | 1.46674       |

From Figures 6 and 7, it is seen that under uniform shading conditions (i.e., patterns-1, 2, and 5), the $P$-$V$ and $I$-$V$ graphs produce only one maximum point. However, when partial shading (i.e., patterns-3, 4 and 6) occurs in the PVS, the $P$-$V$ and $I$-$V$ characteristic graphs start producing multiple maximum points due to the working of the bypass diodes in the system. From the graphs (i.e., patterns-1 to 6), it can be seen that the MPP shifts to the lower left region with the decrease in irradiation and, a decrease in temperature helps to shift the MPP upwards (in Figure 6). Meanwhile, the corresponding PV voltage ($V_{mpp}$) at MPPT will be higher with a high value of peak power under different shading patterns, as observed in Figure 6. A similar analysis can be examined in Figure 7 that the corresponding PV current ($I_{mpp}$) at MPPT will be higher with a high value of peak power.

3.2. Performance assessment of the RIO and PSO algorithms for different benchmark functions

A comparative performance assessment of the RIO and PSO is given in Table 6 for different benchmark functions. In this case study, a minimization problem (i.e., objective function) is considered to get the comparative statistical search performance results of the benchmark functions for 120 numbers of iteration. From Table 6, it can be noticed that the data obtained by the RIO algorithm are better than PSO in terms of mean, standard deviation (SD), and best value ($f_{min}$). Additionally, the convergence characteristic curve for two benchmark functions: Bohachevsky-1 and Langerman-5 is demonstrated in Figure 8. Figure 8 represents that RIO algorithm obtains its global minimal solution for less number of iterations in comparison to PSO. This accomplishment of the RIO algorithm was proved by evaluating the results with that of the PSO for different test functions in [38].

![Figure 8](image-url)
Table 6. Comparative performance indexes of different test functions

| Functions [31]     | DD | Search space | Statistical values | PSO       | RIO*       |
|-------------------|----|--------------|--------------------|-----------|------------|
|                   |    |              | Best \( f_{min} \) | 8.39e-05  | 6.56e-05   |
|                   |    |              | Mean               | 8.40e-05  | 6.61e-05   |
|                   |    |              | SD                 | 9.20e-07  | 8.95e-07   |
| GoldStein-Price   | 5  | [-200, 200]  | Best \( f_{min} \) | 6.63e-06  | 5.93e-06   |
|                   |    |              | Mean               | 6.63e-06  | 5.99e-06   |
|                   |    |              | SD                 | 0.33e-07  | 0.31e-07   |
| Perm              | 5  | [-200, 200]  | Best \( f_{min} \) | 4.86e-07  | 2.74e-07   |
|                   |    |              | Mean               | 4.88e-07  | 2.79e-07   |
|                   |    |              | SD                 | 0.57e-09  | 0.52e-09   |
| Langerman-5       | 5  | [-200, 200]  | Best \( f_{min} \) | 8.75e-06  | 7.41e-06   |
|                   |    |              | Mean               | 8.77e-06  | 7.41e-06   |
|                   |    |              | SD                 | 1.83e-08  | 1.67e-08   |
| Bohachevsky-1     | 5  | [-200, 200]  | Best \( f_{min} \) | 0.00e+0   | 0.00e+0    |
|                   |    |              | Mean               | 0.00e+0   | 0.00e+0    |
|                   |    |              | SD                 | 0.00e+0   | 0.00e+0    |

*DD - Number of design variables or dimension, SD- Standard deviation

3.3. Comparison between PSO and RIO algorithm for MPPT

To ensure satisfactory performance under partial shading, the RIO-based MPPT recognizes the GMPP. For GMPP tracking, the \( V_{m} \) and the \( I_{m} \) are significant for identifying the MPP. The harvested actual PV power \( (P_{pv}) \) of the PVS based on the results obtained from both PSO and proposed RIO algorithms are presented in Figures 9 and 10. The simulation results are carried out under the same patterns as shown in Case-3.1.

Figure 9. PV system output power performance graph
As shown in Figures 9-10, the RIO-based technique tracked the MPP with higher accuracy and extract more power than the PSO from the PV system. The same can be examined in other shading patterns for different values of solar irradiation and temperature. The exact value of the actual power ($P_{pv}$) tracked by the RIO and PSO of the PVS is presented in Table 7, as assessed in Figures 9 and 10. Additionally, in order to evaluate the actual MPPT performance attained by both algorithms, the mathematical formulation for MPPT efficiency ($\eta_{MPPT}$) is represented as follows [7]:

$$\% \eta_{MPPT} = \frac{P_{pv}}{P_{MPPT}} \times 100$$  \hspace{1cm} (7)

where, $P_{MPPT}$ or $G_{p}$ is the maximum achievable power or true MPP of the PV system (maximum power points are shown in Figure 6). $P_{pv}$ is the actual power extracted from the PV array which depends upon the ability of the MPPT to be as close as possible to the true MPP system (Figures 9 and 10).

![Figure 10. PV system output power performance graph](image)

Table 7. Comparative MPPT performance of RIO and PSO

| Pattern  | PSO | Algorithm |
|----------|-----|-----------|
|          | $P_{pv}$ (W) | $\eta_{MPPT}$ (%) | $t_c$ (ms) | $P_{pv}$ (W) | $\eta_{MPPT}$ (%) | $t_c$ (ms) |
| Pattern-1| 234.597 | 98.585 | 113.964 | 236.036 | 99.190 | 58.451 |
| Pattern-2| 135.903 | 98.538 | 113.819 | 136.779 | 99.174 | 58.459 |
| Pattern-3| 113.651 | 98.097 | 124.856 | 114.502 | 98.832 | 67.208 |
| Pattern-4| 75.128  | 98.113 | 124.572 | 75.703  | 98.865 | 67.211 |
| Pattern-5| 246.769 | 98.584 | 113.963 | 248.288 | 99.191 | 58.453 |
| Pattern-6| 78.922  | 98.115 | 124.857 | 79.526  | 98.866 | 67.203 |

It is true that the higher the MPPT algorithm’s accuracy, the higher the $\eta_{MPPT}$. The tracking efficiency of the MPPT algorithms for the PV system is shown in Table 7. From the above results, it can be concluded that the proposed RIO technique has a good tracking performance.
competency as compared to the PSO-based MPPT technique. Moreover, it can be observed that $\eta_{MPPT}$ varies with change in partial shading pattern due to the search behavior of the optimization algorithms being random in nature to track the optimal point/solution. Additionally, the convergence speed (i.e., searching process time) is the time that the PV system takes to achieve the steady-state value of $P_{pv}$. The searching process time ($t_c$) of the PSO algorithm (Table 7) is more than that of the RIO technique for MPPT, as studied in Figures 9 and 10. Furthermore, it can be seen that the value of $t_c$ is higher for the partial shading scenario as compared to the symmetrical irradiation on the PV panel.

5. Conclusions and Future Work

In this work, an MPPT technique based on a bio-inspired Roach infestation algorithm is projected to harvest the maximum power from a solar PV under uniform irradiation and PSC uses a step-change in irradiation. The obtained results are examined and evaluated with the PSO algorithm. The results demonstrate that the RIO MPPT contributes better to global maximum power tracking with high accuracy as compared to PSO-based MPPT. In addition, the RIO algorithm is investigated for various benchmark functions and the findings show that RIO is superior to PSO in requirements of computational convergence and optimal solution.

Future research work may be about to investigate the proposed modified RIO algorithm to enhance its search performance for solving different optimization problems. Also, the supremacy of the suggested RIO algorithm can be validated in an experimental hardware platform.

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Abbreviations: The following abbreviations are used in this manuscript:
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