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A Scheme-based Review of MPPT Techniques with Respect to Input Variables Including Solar Irradiance and PV Arrays' Temperature

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ABSTRACT Maximum power point tracking (MPPT) techniques have been vastly researched and developed in order to obtain the maximum terminal power of photovoltaic (PV) arrays in the solar renewable energy system. The aim of this paper is to present a new principal scheme-based review of the categorised MPPT methods (conventional, novel, and hybrid) with respect to the deployment of their input variables (solar irradiance, PV arrays' temperature, and PV arrays' terminal voltage and current), where MPPT methods are categorised to six different schemes. For each scheme, previous MPPT studies are extracted from literature and analysed. Then the critical benefits and limitations of the six presented MPPT schemes are compared and discussed. It is concluded that those MPPT schemes deploying the measured external variables would be able to track the global maximum power point with high reliability; however, their implementation cost and applicability remains as a challenge due to increasing the sensor deployment cost and complexity. The conclusion of this paper will help new researchers to deliberately select an appropriate MPPT scheme based on their projects' objectives and limitations, prior to selecting an optimisation algorithm for MPPT.

INDEX TERMS Solar photovoltaic, Maximum Power Point Tracking (MPPT), solar renewable energy system, power conversion efficiency.

I. INTRODUCTION

In comparison with the non-renewable energy systems, solar renewable energy system (SRES) does produce less amount of negative environmental impacts such as air pollution (greenhouse gas emission) but its power efficiency is highly depended on the external (environmental) impacts. Since these impacts and conditions are variable, solar renewable energy (SRE) is not a fixed voltage or current source [1].

Maximum power point tracking (MPPT) is employed in order to automatically track the maximum power point (MPP) of photovoltaic (PV) arrays in SRES. Resulting from sudden and fast environmental changes, the MPP as well as the output I-V curve of PV arrays are also changed considerably.

Therefore, the sensed external variations and their impacts should be considered in designing and implementing of the MPPT methods. In general, sudden variations of solar irradiance (λ), variations of PV array's temperature (T), and partial shading condition (PSC) have been researched as the most important external impacts in SRES [2].

Researchers have tried to present various types of high accuracy MPPT methods to control the internal and external impacts of SRES, and a wide range of analytical and numerical MPPT algorithms have been employed [3]–[8]. They have mostly optimised the sensed PV arrays' terminal voltage (V) and current (I). However, some research projects applied the sensed λ and T in the MPPT methods.

There are also a considerable number of MPPT overview and comparative surveys, where the MPPT algorithms have been mostly classified as the conventional and novel methods [9]. A combined approach of two or more conventional and/or novel MPPT algorithms is also categorised and called as hybrid MPPT method [7].

The conventional MPPT methods are also categorised as

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indirect (offline) and direct (online) approaches [2], [10]. A comprehensive history of MPPT methods was presented in the first chapter of [2], and a comprehensive review and critical analysis of MPPT methods was presented in [11], [12] as well as in the fourth chapter of [5].

Although previous comprehensive and comparative review studies have been trying to categorise and compare the MPPT methods based on the type of optimisation algorithm being used, a different review study capable of classifying and analysing the existing well-known MPPT methods with respect to their input variables is still required.

To this end, this paper presents a scheme-based review of the existing conventional, novel, and hybrid MPPT topologies with respect to the deployment of their sensed inputs, λ, T, V, and I. In section II, a brief review of external impacts on the SRES's performance is presented. In section III, six different MPPT schemes are classified and reviewed. In section IV, a comparison based on the main criteria, limitations, and benefits of each scheme, is performed and discussed. Recommendations to develop MPPT schemes and unravel their limitations are presented in section V, and a conclusion accompanied with future research suggestions are discussed in section VI.

II. EXTERNAL IMPACTS

External impacts are generally described as the environmental variations and disturbances affecting the SRES's performance, regardless of the SRES's dynamic characteristics including the non-linear dynamic of solar PV arrays, the variations of power conversion circuit parameters, and the variations of load. External impacts are usually unfavourable, fast, and unforeseeable. A wide range of optimisation algorithms and control system techniques have been used to control these variations. As mentioned, external variations affecting the SRES's performance include;

- Variations of λ, a rate of income amount of solar energy on horizontal PV arrays.
- Variations of T, temperature of PV arrays' surface (solar PV cells' temperature).
- PSC, resulting from either cloudy condition or dusty surface of the PV arrays [3], [10], [13].

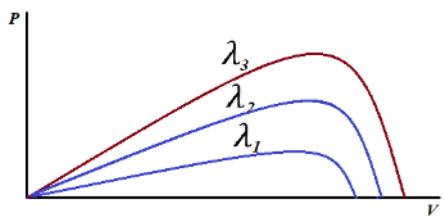

FIGURE 1. PV array's P-V curve shown for three levels of solar irradiance (λ), where $\lambda_1 < \lambda_2 < \lambda_3$.

As shown in Figure 1, the higher λ, the higher terminal power (P) a solar PV array can deliver, where $\lambda_3(W/m^2)$ results in a higher MPP than $\lambda_2(W/m^2)$, sequently higher MPP than $\lambda_1(W/m^2)$. Differently, as shown in Figure 2, the higher PV array's temperature, the lower power a PV array may deliver, where $T_1(^\circ C)$ results in a higher MPP than $T_2(^\circ C)$ and $T_3(^\circ C)$.

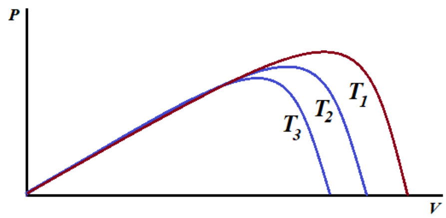

FIGURE 2. PV array's P-V curve shown for three levels of PV arrays' temperature (T), where $T_1 < T_2 < T_3$.

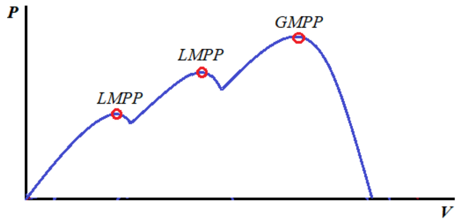

FIGURE 3. PV array's P-V curve shown for rapidly variations of external impacts.

Also, as per shown in Figure 3, it has been resulted that under rapid change of the external impacts, multiple local MPPs (LMPPs) may occur, when there is always one desired global MPP (GMPP), the desired MPP representing the highest PV array performance [14].

III. EXISTING MPPT SCHEMES IN SRES

As discussed, a wide range of control and optimisation algorithms have been used in order to obtain the GMPP in the SRESs, as shown in Figure 4, where each technique has employed some of the sensed input variables (shown as MPPT inputs in Figure 4).

In this section, six MPPT schemes are classified through combining the MPPT techniques and MPPT input variables. Each scheme is independently presented and discussed. As mentioned, this paper is going to review MPPT schemes in SRES, where to further study about various types of DC-DC converters in SRES, the resources [15]–[17] are recommended.

A. CONVENTIONAL MPPT METHODS

Conventional MPPT methods are categorised as indirect (offline) and direct (online) approaches.

Fractional open circuit voltage (FOCV) and fractional short circuit current (FSCC) are the commonly used indirect MPPT methods, where V and I are computed based on a ratio of the open circuit voltage (V_{oc}) or the short circuit current (I_{sc}) in the offline state [2].

Perturb and observe (P&O) and incremental conductance (INC) algorithms, derived from hill climbing (HC), local search family optimisation algorithms, have been presented

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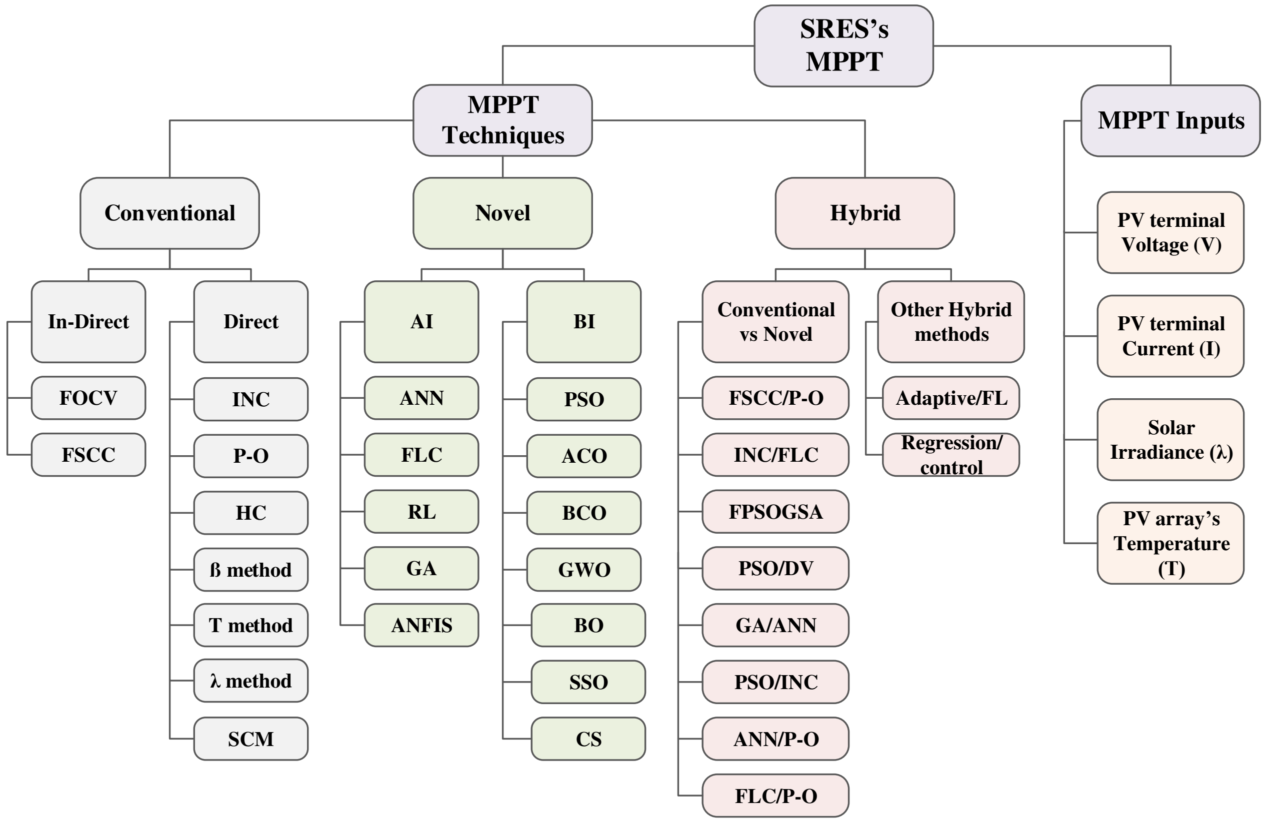

FIGURE 4. A flowchart of the existing MPPT techniques and MPPT input variables.

as direct MPPT methods [2]. The main advantages of these methods are known as their algorithms' simplicity and low implementation cost.

1) Scheme 1, conventional MPPT, input variables: V and I

The principal scheme 1 is depicted in (Figure 5 (Scheme 1)). Since SRES is dynamically non-linear, it may not accurately respond to the unfavourable, fast, and non-linear input variations. Majority of conventional MPPT algorithms control and optimise this non-linear system without taking advantage of feed-forward or feedback loops to observe and control the external variations, λ and T. In other words, the conventional MPPT methods are unable to quickly reset their algorithms' parameters and constraints reacting to the sudden external changes and disturbances being usually applied in SRES. Then they are susceptible to get trapped in the LMPPs being resulting in losing power during the power tracking process [3].

Both P&O and INC algorithms follow the perturbation techniques based on step-measuring and comparing the V, I, and P until reaching the MPP [14]. As mentioned, sudden external variations would finally result in the sudden changes of the PV terminal power. In this crucial situation, the conventional direct and indirect MPPT methods often suffer from their disability to track the GMPP, where P&O and INC algorithms may drop in an instable loop. For example, in accordance with Figure 6, P&O algorithm constantly perturbs $\Delta V = V_t - V_{t-1}$, computes $\Delta P = P_t - P_{t-1}$, and tracks MPP based on ΔV and ΔP (graph 1), when a big $\Delta\lambda$ immediately affects and reshapes the PV's output I-V curve (graph 2) locating P_t (Point B) and P_{t-1} (Point A) in different sides of MPP. In addition, the algorithm is still oscillating around the MPP even after reaching there. Although, oscillation around MPP can be controlled by reducing the step size $\Delta t = t - (t-1)$, it would negatively result in increasing the tracking time. In this condition, the algorithm does not work efficiently.

In [18], it was tried to modify the P&O algorithm by adding a dynamic switching circuit to track the fast external changes. In [19], some control based MPPT methods such as slide control mode (SCM) and ripple correlation control (RCC) were classified as conventional MPPT methods and further reviewed in [14], [20]. In SCM based MPPT [20], the power converter switching function u works based on the fact that $dP/dV > 0$ is placed on the left side of the MPP, and $dP/dV < 0$ is placed on the right side of MPP. The control term S is defined as;

$$S = dP/dV = I + V\frac{dI}{dV} \tag{1}$$

Where the open switch ($u = 0$) and the close switch ($u = 1$)

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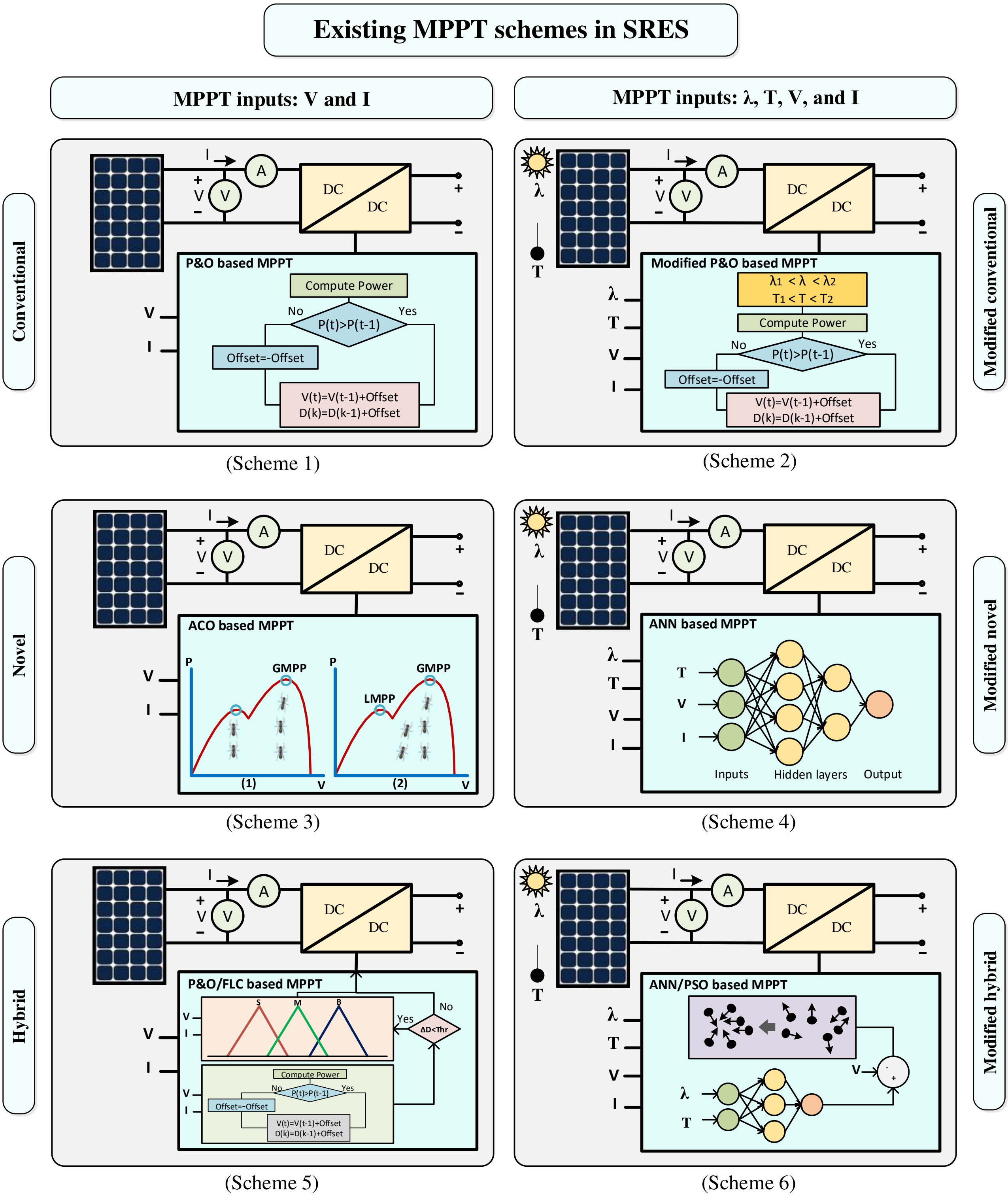

FIGURE 5. MPPT Schemes.

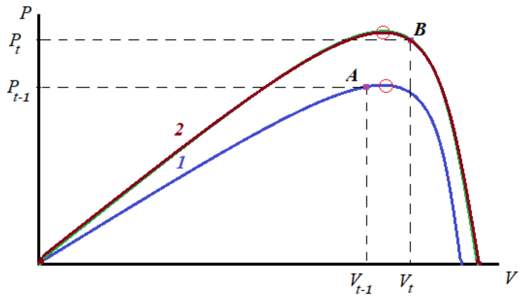

FIGURE 6. Divergence in conventional MPPT algorithm.

are given as (2).

$$\begin{aligned} u &= 0 \quad S \geq 0 \\ u &= 1 \quad S < 0 \end{aligned} \tag{2}$$

2) Scheme 2, modified conventional MPPT, input variables: λ, T, V, and I

The principal scheme 2 is depicted in (Figure 5 (Scheme 2)). Although many steps have been taken in order to optimise the conventional MPPT methods to control the external variables, majority of the conventional MPPT methods employ the non-linear dynamic model of PV arrays in their computations, when it can still result in some unwanted power oscillations regardless of the accuracy of employed methods. A possible solution is due to directly applying the sensed λ and T by modifying the conventional MPPT methods.

For example, in the Temperature MPPT method , variable T has been applied to the FOCV method [4], [10].

$$V_{mpp}(t) = k_{ocv} \times V_{oc}(t) \tag{3}$$

$V_{mpp}(t)$ represents the output voltage at MPP, k_{ocv} defines as open circuit voltage coefficient, and $V_{oc}(t)$ represents the open circuit voltage.

$$V_{mpp}(t) = V_{mpp}(T_{ref}) + T_{k_{V_{oc}}}(T - T_{ref}) \tag{4}$$

$V_{mpp}(T_{ref})$ represents the output voltage at MPP, T_{ref} is reference temperature, and $T_{k_{V_{oc}}}$ defines as temperature coefficient of open circuit voltage. Although this method may reduce the oscillation around MPP due to measuring and tracking the sudden variations of T, it still requires offline measuring of $V_{oc}(t)$. Moreover, temperature sensing can be not only impractical in the large-scale SRESs but also problematic due to its implementation and calibrations' complexities.

As another suggestion, (4) can be modified by adding the λ variable or a coefficient of that. However, in other conventional MPPT methods, λ and T were employed to track the optimum range of GMPP, assisting the conventional MPPTs [21].

B. NOVEL MPPT METHODS

Various novel (soft-computing) optimisation algorithms were employed in order to obtain the GMPP in SRES. Novel optimisation algorithms including artificial intelligence (AI) and biologically inspired (BI) were used in order to obtain the GMPP [2], [22]. In this paper, novel MPPT methods are categorised as their interaction with λ and T.

1) Scheme 3, novel MPPT, input variables: V and I

The principal scheme 3 is depicted in (Figure 5 (Scheme 3)). In this scheme, novel MPPT methods including AI and BI algorithms are employed to obtain the GMPP by optimising V and I. In [23], cuckoo search (CS) was applied to improve the MPPT performance, transient behaviour, and convergence speed. Giving the simulation results for CS, particle swarm optimisation (PSO), and P&O algorithms, the main advantages of CS were resulted as very low oscillation around MPP at steady-state condition and high ability to handle the PSC. The CS algorithm complexity was lower than PSO but higher than P&O. Also, the hardware validation and low implementation complexity and cost of this method were discussed.

Ant colony optimisation (ACO) algorithm [24] was verified as having a better performance to find GMPP in compare to the P&O and the constant voltage tracking (CVT) algorithms as well as being simple in compare to the PSO algorithm in terms of iterations number and independency to the initial conditions.

In addition, in other studies, bee colony optimisation (BCO) algorithm [25], bat optimisation (BO) algorithm [26], salp swarm optimisation (SSO) algorithm [27], (all belong to the BI algorithms), were employed in the solar MPPT units mostly for their capability of tracking and identifying the GMPP under PSC. However, their efficiency, implementation complexity, and applicability in the large-scale solar SRES need to be further investigated.

Among AI and machine learning algorithms, reinforcement learning (RL) was employed to minimise the set-up time and to track the MPP for different PV sources (different PV's characteristics) under various operating conditions [28].

Also, in [29], fuzzy logic control (FLC) based MPPT method was proposed and highlighted due its ability to rapidly respond to external variations and its stability with respect to circuit parameters' variations. However, the difficulties of constructing FLC system was mentioned, when the reliability of FLC is also depended on expert knowledge and fuzzy parameters such as membership functions.

2) Scheme 4, modified novel MPPT, input variables: λ, T, V, and I

The principal scheme 4 is depicted in (Figure 5 (Scheme 4)). In this scheme, λ and T are also employed as inputs to novel MPPT. There are a few studies in literature research on this MPPT scheme.

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In [30], a novel BI optimisation method named memetic salp swarm algorithm (MSSA) by using a dataset of λ and T was presented to obtain GMPP under fast varying-weather condition, where a fast and stable convergence was obtained. In addition, the variability (power fluctuation) under step change of λ was obtained about 34% for MSSA and above 66% for other investigated MPPT methods (INC, genetic algorithm (GA), PSO, gray wolf optimisation (GWA), etc).

Some of other novel algorithms capable of being implemented in the form of this MPPT scheme were reviewed in [14], [19], [20].

C. HYBRID MPPT METHODS

Various hybrid optimisation algorithms by combining the conventional MPPT algorithms and/or the novel MPPT techniques have been employed in SRESs. However, there are a few hybrid linear or non-linear control system based MPPT methods in literature [31].

1) Scheme 5, hybrid based MPPT, input variables: V and I

The principal scheme 5 is depicted in (Figure 5 (Scheme 5)). In [32], a switching-based control method was employed to obtain the initial operating point by using FSCC method and to track GMPP by switching to the P&O algorithm. This method reduced the oscillation around MPP in face with sudden external variations by resetting the algorithm parameters regularly and estimating the GMPP in every cycle, however its dependency on the offline tracking was increased.

FLC has been employed in some studies to improve the performance of conventional MPPT methods like P&O and INC by controlling their undesired disturbances (including fast changes of λ) [33], [34]. It was mostly used to optimise the duty cycle of DC-DC converters either by fuzzification and optimising the error between instantaneous conductance and incremental conductance [33] or by optimising the conventional algorithms' derivations [34]. The proposed methods resulted the high power efficiency and fast GMPP tracking as well as low power oscillation in the steady-state condition though the algorithm complexity was increased.

In addition, artificial neural network (ANN) algorithms were combined with the conventional MPPT methods such as P&O and INC [35]–[37]. They were employed to either determine the initial V_{mpp} or to optimise the output of conventional MPPTs. Other hybrid MPPT methods including novel/novel and conventional/conventional MPPT algorithms are also reviewed in Table 1.

2) Scheme 6, modified hybrid MPPT, input variables: λ, T, V, and I

The principal scheme 6 is depicted in (Figure 5 (Scheme 6)). This scheme is expected as to be the most accurate MPPT scheme, where the external impacts (λ and T) are also applied in the high efficient hybrid MPPT algorithms. The algorithm and implementation complexity as well as other features of this MPPT scheme are reviewed in Table 1.

In [38], a combination of an adaptive calculation block for calculating the reference voltage point of MPPT (by using λ and T measurements) and a FLC block for adjusting the duty cycle of pulse width machine (PWM) was presented, where a high accuracy (above 99% efficiency) and low oscillation MPPT was obtained by four and five times faster than the conventional P&O and INC algorithms, respectively 28% faster than single FLC based MPPT. However, the implementation cost and complexity factors were mentioned as its drawbacks.

In [39], an ANN vision-based MPPT system combined with Back-stepping controller under PSC was designed. The artificial vision was used to identify the PSC and λ variations in order to provide the maximum reference voltage and maximum power, where a robust and non-linear back-stepping controller was employed to regulate the DC/DC converter by controlling the differential error between the PV output voltage measured by voltage sensor and maximum reference voltage obtained by ANN. The proposed MPPT method successfully tracked the GMPP under various levels of PSC and λ variations. It was discussed that the required webcams and image processing system would cost less than employing other relevant environment sensing methods but its complexity and applicability in the large-scale SRES as well as required embedded processor were not investigated.

In [40], a novel MPPT algorithm by using the ANN based on fuzzy particle swarm optimisation gravitational search algorithm (FPSOGSA), (A combination of fuzzy based gravitational search algorithm (GSA), from heuristic methods, and PSO algorithm) was presented, prototyped, and tested. Simulation and experimental results confirmed reducing power oscillations and stabilising the reference voltage around MPP rather than conventional MPPT methods. λ and T were measured through using the solar irradiance and PV temperature sensors and the applicability of the proposed method was shown using a TMS320F28335 digital signal processor (DSP).

In [10], the measurements of λ and T were employed to estimate the PSC, where the measurements of λ was employed to modify the FOCV combining with P&O to deliver the GMPP. High GMPP tracking efficiency was obtained by comparing the proposed MPPT method with other conventional MPPT methods.

IV. COMPARISON AND DISCUSSION

In previous MPPT review studies [2], [7], [8], [11], [12], [14], [19], [20], [26], [41]–[46], the performance of various MPPT methods have been discussed and compared.

In this paper, a comparative review of the presented MPPT schemes is delivered through Table 1. Where, the significant criteria to indicate the performance, efficiency, complexity, and implementation cost of the six presented schemes are discussed below.

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A. POWER CONVERSION EFFICIENCY

Power efficiency is the most important MPPT's factor which represents the quality of the employed MPPT method. Apart from other factors such as implementation cost and complexity of the novel and hybrid MPPT methods, their efficiency has been often approved as higher than the efficiency of conventional MPPT methods [7]. In general, Novel (soft-computing) based MPPT methods are accurate and their tracking efficiency and speed is high [44]. MPPT power efficiency, represented in Table 1, is computed in the steady-state of GMPP, when the performance of MPPT depends on other factors as well. According to the Table 1, scheme 1 has a lower efficiency than other MPPT schemes due to the often employing the simple algorithms, those which are not able to track the fast external variations and may get trapped in the LMPPs, where a considerable amount of power would be lost. The efficiency of other schemes are quite high due to using either accurate algorithms or sensing and tracking the fast external changes.

B. ANALOG/DIGITAL

The MPPT methods are implemented through either analog or digital circuit processers. Despite some of the conventional MPPT methods, most of the novel and hybrid MPPT methods require to be designed and experimented on the digital embedded systems. When, in the MPPT schemes 2, 4, and 6, a high volume of complex computations are added because of the external variables' measurements, data acquisition, and data processing.

C. PERIODIC TUNING

Some MPPT techniques may require periodic tuning to update their training parameters. It can be done due to the updating of AI algorithms such as ANN and FLC which are employed to either obtain the GMPP, schemes 3 and 5 or to train the external variables to estimate a reference voltage for MPPT algorithm, schemes 4 and 6.

D. TRACKING (CONVERGENCE) SPEED

Tracking speed of the MPPT technique defines as its speed to reach the MPP. A high tracking speed does not necessarily accompanied with a high power efficiency. For example, in the P&O MPPT method, high tracking speed involves increasing in the perturbation size which then results in a poor tracking efficiency. In general, both accuracy and complexity of a MPPT algorithm are the main factors affecting the tracking speed. Moreover, the number of sensors are used, their data acquisition and measurement process, and their computational complexity can affect the tracking speed. Also, the delay during start up may affect the tracking speed of some MPPT methods [47]. Taking into consideration the above, it is concluded that schemes 4, 5, and 6, requiring sensing and almost complex and hybrid algorithms, may take time to track the MPP though the type of algorithm is used is still effective. Conventional MPPT methods, scheme 1, are quite slow because of their incapability to find GMPP.

E. ALGORITHM COMPLEXITY

Size and number of the MPPT input and output variables, processing time, number of optimisation's parameters, number of steps taken to obtain the GMPP, and other analytical parameters are to be considered to compute and to analyse the complexity of MPPT optimisation algorithms. It has been computed that the conventional MPPT algorithms, schemes 1 and 2, are less complicated than the novel and hybrid based MPPT algorithms, schemes 3, 4, 5, and 6. However, the complexity of scheme 2 is also depended on sensing process's complexity.

F. STEADY-STATE OSCILLATION

A critical factor in selecting the appropriate MPPT method is known as its stability around MPP. In fact, after reaching the MPP, it is very important that the MPPT algorithm can control the power oscillation. The big oscillations around MPP may result in losing power and decreasing the power efficiency. The accuracy of selected algorithm as well as considering the external impacts play the critical role to control the oscillation in steady-state condition. Hence, as discussed, schemes 2, 4, and 6 are strongly able to control the oscillations around MPP.

G. IMPLEMENTATION COST

When it comes to investigate the limitations of MPPT methods, implementation cost as well as hardware requirements must be considered. Type of software and processors required, type and number of sensors required, and whether analog or digital implementation is desired, can determine the cost of the selected MPPT method. It may also include the costs of training the operators and MPPT maintenance. In previous review and comparative studies, in general, conventional MPPT methods are cheaper and easier to implement, while novel (soft-computing) MPPT methods require the high performance software and processors [44].

Moreover, conventional MPPT methods can be implemented by analog processing which is cheaper than novel MPPT methods requiring digital processing [7].

The scheme-based MPPT classification presented in this paper can easily facilitate future research to identify the implementation cost of every MPPT method which they wish to work on. According to the Table 1, the implementation of those schemes 2, 4, and 6 mainly using both novel MPPT algorithms and sensing λ and T is quite high.

Besides complicated algorithms being used in the schemes 2, 4, and 6, their effort to consider the external variations' impacts would naturally result in the high complexity and cost. Measuring Climate change impacts especially in the large scale SRESs cannot be an easy and economical process. It would also increase the disturbance and noise of the SRES requiring further control.

Moreover, some of the novel MPPT methods employed in schemes 3, 4, 5, and 6 require the periodic training and tuning, which exceeds the complexity of MPPT.

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TABLE 1. Comparison of various MPPT methods.

	MPPT Techniques	Efficiency	Analog /Digital	Periodic tuning	Convergence speed	Algorithm complexity	Steady-state oscillation	Implementation cost (large scale)	Sensors	Scheme
1	FVOC [19]	Low	Both	Yes	Medium-High	Low	High	Low	V	**1**
2	FSCC [8], [45]	Low	Both	Yes	Medium-High	Medium	High	Low	I	**1**
3	P&O [8]	Medium	Both	No	Varies	Low	High	Low	V and I	**1**
4	INC [8]	Medium-High	Digital	No	Varies	Medium	Medium	Medium	V and I	**1**
5	β MPPT [4], [45], [48]	High	Digital	Yes	High	High	Low	Medium	V and I	**1**
6	HC [8]	Medium	Both	No	Low	Medium	Medium	Medium	V and I	**1**
7	Modified P&O [18]	High	Both	No	High	Medium	-	Low	V and I	**1**
8	SCM [14], [20]	-	Digital	No	High	Medium	-	Medium	V and I	**1**
9	RCC [20]	-	Analog	No	High	Medium	-	Low	V and I	**1**
10	Temperature (T) method [4], [20], [45]	High	Digital	Yes	Medium	High	Low	High	V and T	**2**
11	I and T measurement [21]	High	Digital	Yes	High	Medium	Low	Medium-High (regular update)	I and T	**2**
12	LCC [20]	-	Digital	Yes	High	-	-	Medium	λ	**2**
13	I_{mpp}, V_{mpp} computation [20]	-	Digital	Yes	-	-	-	Medium	T and λ	**2**
14	PSO [8], [38], [48], [49]	High	Digital	No	Medium-High	Medium	Varies	Medium	V and I	**3**
15	FLC [29], [38], [43], [50]	Medium-High	Digital	Yes	Medium-High	Medium-High	Varies	Medium-High	V and I	**3**
16	ANN [38], [49], [50]	High	Digital	Yes	Medium-High	High	Varies	Medium-High	V and I	**3**
17	CS [23]	High	Digital	Yes	Varies	Medium	Low	Low-Medium	V and I	**3**
18	Simulated Annealing (SA) [51]	High	-	No	Varies	Medium	Low	-	V and I	**3**
19	RL [28]	High	Digital	No	High	Medium	Low	-	V and I	**3**
20	ACO [49]	High	Digital	No	High	Medium-High	Low	Medium	V and I	**3**
21	BCO [25]	High	Digital	No	Very High	Medium	Low-Medium	-	V and I	**3**
22	BO [26]	High	Digital	No	High	Medium-High	Low	Medium	V and I	**3**
23	SSO [27]	High	Digital	No	Very High	High	-	Medium	V and I	**3**
24	GA [50]	High	Digital	No	High	High	Low	Medium	V and I	**3**
25	DE [50], [52]	High	Digital	No	High	Low-Medium	Low	Medium	V and I	**3**
26	MSSA [30]	Very High	Digital	Yes	High	High	Very Low	-	V, T, and λ	**4**
27	ANN [19]	Very High	Digital	Yes	High	Medium	Low	High	T and λ	**4**
28	ANFIS [19]	Very High	Digital	Yes	High	High	Low	High	T and λ	**4**

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29	BSC [14], [20]	-	Digital	No	Varies	-	-	High	V, I, T, and λ	**4**
30	Lookup Table [20]	-	Digital	Yes	High	-	-	Medium	V, I, T, and λ	**4**
31	PSO/INC [45]	High	Digital	No	High	Low	Low-Medium	Medium	V and I	**5**
32	ANN/P&O or INC [35], [36], [48]	High	Digital	Yes	High	Medium	Low	Medium	V and I	**5**
33	PSO/FLC [8], [53]	High	Digital	Yes	High	High	Low	High	V and I	**5**
34	PSO/DV [54]	-	Digital	Yes	High	High	-	-	V and I	**5**
35	FSCC/P&O [48]	High	Both	Yes	High	Medium	Low-Medium	Low	V and I	**5**
36	INC/FLC estimator [33]	High	Digital	Yes	High	Medium	Low	-	V and I	**5**
37	PSO/P&O [48], [55]	High	Digital	No	High	Low-Medium	Low	Medium	V and I	**5**
38	FLC/P&O [48]	High	Digital	No	High	Medium	Low	Medium	V and I	**5**
39	GWO/P&O [48]	High	Digital	No	High	Medium	Low	Medium	V and I	**5**
40	ACO/P&O [48], [56]	High	Digital	No	Very High	Medium	Low	Medium	V and I	**5**
41	P&O/AIDSM [57]	High	Digital	No	Very High	Medium	Low	Medium	V and I	**5**
42	N-FL [19]	Very High	Digital	Yes	High	High	Low	High	V, T, and λ	**6**
43	FPSOGSA [40]	High	Digital	Yes	High	High	Low	-	V, T, and λ	**6**
44	GA-optimised ANN [45]	High	Digital	Yes	High	High	Low	High	V, T, and λ	**6**
45	Adaptive calculation/FLC [38]	High	Digital	Yes	High	Medium	Low	High	V, T, and λ	**6**
46	Regression/Nonlinear control [31]	High	Digital	No	High	High	Low	High	V, T, and λ	**6**
47	Vision based control [39]	High	Digital	Yes	High	High	Low	High	V, I, T, and λ (Image processing)	**6**
48	FOCV/P&O [47]	High	Digital	Yes	High	Medium	Low	Medium-High	V, I, and T	**6**
49	SVM/P&O [58]	High	Both	Yes	High	High	Low	Medium (offline data), High (regular update)	V, I, and λ	**6**
50	Modified FOCV/P&O [10]	High	Both	Yes	High	Medium	Low	High	V, I, T, and λ	**6**

Since the constraints of the system are changed regularly and often quickly, it is not efficient to tune the controller frequently, as it is also accompanied with increasing the implementation cost.

Therefore, implementation cost factor plays an important role in designing the MPPT methods, where the majority of industrial MPPT control units are designed based on the conventional methods with some modifications. Indeed, when it comes to research, the main effort is to deliver a high performance method using the accurate optimisation and control methods, while on the other side, when it comes to the product's manufacturing and marketing, the big concern turns to implementation complexity and manufacturing cost.

V. RECOMMENDATION

Tracking the MPP of a large scale SRES in a region with fast and unforeseeable weather and climate change conditions demands the measurements of λ and T. In this situation, a practical solution to minimise costs and complexity is to research on network sensing methods, sensor reduction and data fusion techniques, and vision-based algorithms which may decrease the number of sensors required and correspondingly increase the measurement's accuracy.

Authors of this paper would also recommend further research on new techniques which can be efficient and applicable, where the external impacts are also considered in MPPT methods without concern for sensing cost and complexity. Some likely suggestions are listed below.

- Employing the inverse-modelling and parameter estimation techniques to estimate the external variables from PV terminal voltage and current.
- Employing the predictive control-based methods instead of MPPT conventional and soft-computing algorithms.
- Applying some extra constraints in existing MPPT methods by taking advantage of feed-back and feed-forward control loops.
- Developing the PV array dynamic model using the accurate model identification methods.
- Employing the image processing methods to estimate the external variations by processing their effects on PVs' surface using a few webcams and processor, instead of installing a sensor network to measure λ, and T in large-scale SRESs.
- Training the offline climate data to predict the external variations.

VI. CONCLUSION

MPPT unit is in charge of controlling and optimising the maximum power efficiency in the SRESs. In previous research studies, employing a vast range of optimisation algorithms has classified the MPPT methods as conventional, novel, and hybrid. Since the solar PV arrays behave like a non-linear dynamic systems, the aim of previously presented MPPT methods has been to control the sudden disturbances in the system resulting from sudden external variations such as solar irradiance (λ) and PV arrays' temperature (T). Many MPPT review studies were also presented in the literature, while they all have categorised the MPPT methods based on the type of optimisation algorithm.

- This paper presented a new perspective in classifying the solar MPPTs based on their principal schemes with respect to deployment of the sensed PV arrays' terminal voltage (V) and current (I), λ, and T.
- A combination of the sensed input variables of MPPT unit (λ, T, V, and I) and the MPPT optimisation methods (conventional, novel, and hybrid) created six different MPPT schemes.
- For each scheme, the previous MPPT techniques were extracted from literature and reviewed, where their benefits and limitations were also extracted and discussed.
- The classified schemes were mainly compared based on their performance of tracking speed, controlling the external variations and steady-state oscillation, and delivering the maximum power efficiency, as well as other significant features such as their algorithm complexity and implementation cost in large-scale SRESs.
- Scheme 1: Conventional MPPTs (input variables: V and I) are quite easy to implement however they may not track the GMPP efficiently.
- Scheme 2: Modified conventional MPPTs (input variables: λ, T, V, and I) are more accurate but quite expensive to implement.
- Scheme 3: Novel MPPTs (input variables: V and I) are accurate with sometimes complex computations as well as uncertainty in tracking GMPP under sudden external variations.
- Scheme 4: Modified novel MPPTs (input variables: λ, T, V, and I) are quite accurate with expensive implementation and complex computations.
- Scheme 5: Hybrid MPPTs (input variables: V and I) are more accurate than previous schemes whereas they might still suffer from tracking GMPP under sudden external variations.
- Scheme 6: Modified hybrid MPPTs (input variables: λ, T, V, and I) are the most accurate MPPT methods with complex computations and high implementation cost.
- In general, it was concluded that schemes 2, 4, and 6 considering the measured external variables (λ and T) are able to track the GMPP with high reliability. However, their implementation cost and applicability in the large-scale SRES is still a concern due to the sensor deployment cost and complexity of λ and T.
- To avoid these drawbacks, researchers have tried to develop schemes 1, 3, and 5 by employing a wide range of control and optimisation methods. However, the main drawback of these schemes remains as not to observe the external impacts when a large-scale non-linear system, SRES, is controlled.

Taking all the aforementioned points into account, it can be concluded that despite many MPPT methods being previously researched in the form of each presented scheme in this paper, selecting the best MPPT controller might be still a trade-off between benefits and limitations. However, the new trend in classifying SRES's MPPT schemes presented in this paper would be able to provide a comprehensive view to the future researchers, those who are firstly looking to familiarize themselves with the dimension of their work on the SRES's MPPTs, to determine the advantages and disadvantages of sensing the external variations based on their project's objectives and limitations, to select the best practical and accurate MPPT algorithm, and to estimate the applicability of their MPPT method in the industry.

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