Abstract: Distributed generators (DGs) have emerged as an advanced technology for satisfying growing energy demands and significantly mitigating the pollution caused by emissions. Microgrids (MGs) are attractive energy systems because they offer the reliable integration of DGs into the utility grid. An MG-based approach uses a self-sustained system that can operate in a grid-tied mode under normal conditions, as well as in an islanded mode when grid disturbance occurs. Islanding detection is essential; islanding may injure utility operators and disturb electricity generation and supply because of unsynchronized re-closure. In MGs, an energy management system (EMS) is essential for the optimal use of DGs in intelligent, sustainable, reliable, and integrated ways. In this comprehensive review, the classification of different operating modes of MGs, islanding detection techniques (IDTs), and EMSs are presented and discussed. This review shows that the existing IDTs and EMSs can be used when operating MGs. However, further development of IDTs and EMSs is still required to achieve more reliable operation and cost-effective energy management of MGs in the future. This review also highlights various MG challenges and recommendations for the operation of MGs, which will enhance the cost, efficiency, and reliability of MG operation for next-generation smart grid applications.

Keywords: demand response; energy management; islanding detection; microgrid

1. Introduction

To meet increasing energy demands, most governments and policymakers are searching for alternative energy sources because of growing environmental concerns, the continuous depletion of fossil fuels, and the high cost of traditional energy sources. Renewable energy sources (RESs), such as wind and solar energy, do not generate emissions and cause low levels of pollution. Electricity generation from wind and solar energy meets more than 20% and 8%, respectively, of the total power demands in some countries, which means it can exceed the local power demand [1]. Figure 1 illustrates the market share of primary energy sources in global energy supply over a period of 200 years, which shows the efforts made regarding systematically decarbonizing the global energy system [2]. Global energy systems are progressively becoming less carbon-intensive and involving more RESs. By 2050, it is forecasted that the global energy system could become more efficient while connecting and distributing electricity to automobiles, factories, and buildings that rely on a modern, secure, and resilient electricity system. However, unlike traditional power generation, RESs, especially wind and solar energy, provide a variable energy supply depending on the weather conditions. Thus, the uncertainty and inconsistency of RESs should be considered when estimating their power generation capacity. As a solution to this problem, energy storage technologies such as batteries are typically used. Because of the current, massive deployment of RESs, the operation and economical schemes concerning energy storage and renewable technologies have gained more importance. RESs are typically used to form microgrids (MGs) to meet consumer needs. This helps in attaining an effective
shift from traditional grids into intelligent ones, a reliable and uninterrupted power supply, and a two-way controlled power flow, in addition to improving power quality (PQ) and protecting the environment [3].

One main feature of MG technology is that it can operate in both grid-tied and islanded modes. The proliferation of renewable source-based distributed generators (DGs) continues with the increasing acceptance of MGs. The diverse deployment capability of MGs offers several advantages, such as an increase in the integration of DGs into the grid, efficiency improvement, cost reduction, and risk and emission reductions [4]. However, MGs still face some challenges. For example, they require innovative management and control strategies because traditional strategies cannot continuously respond to the dynamic behavior of MGs [5]. Therefore, an appropriate control approach is required to assure smooth power switching in MGs, particularly under islanding conditions. The control scheme must also enhance the PQ of MGs and control the phase angles, frequency, and voltage variations to maintain them within the desirable limits. The detection of islanding is essential for avoiding hazards and PQ problems. Once the MG is detached from the utility grid (UG), the controller can maintain a stable voltage and frequency to transfer sustainable energy to consumers. An energy management system (EMS) is a key supervisory controller in the MG system [6,7]. EMSs are applied to an MG scheme to maintain the energy balance between sources and loads, to deliver better-quality, sustainable, reliable, and clean energy to consumers [8]. In this review, an extensive overview of different aspects of MGs, including their classification, operating modes, islanding detection (ID), and EMS of MGs with the application of numerous optimization techniques, is presented and discussed.

An MG-based literature database is introduced, considering three key objectives:

1. To focus on the classification and modes of operation of MGs;
2. To understand various methods of MG islanding-state detection;
3. To include the maximum number of approaches for implementing MG EMS.

The electronic databases Web of Science, SCOPUS, and Google Scholar were searched by the authors for MG-related peer-reviewed publications, to create a dedicated database. The search was implemented utilizing a combination of keywords. The references were retrieved based on whether the keywords reflected our research objectives; the final research database comprised 173 references from among 808 research articles (Figure 2) over a 20-year timespan (2002–2021), based on the relevance of the research objectives. Among these 173 references, 88% were from peer-reviewed journal articles, 8% were conference proceedings, and 4% were books and websites. Moreover, journal details, such as the publication year, journal impact, and reliability of the reported results/data, were considered while choosing the research papers.
2. General Aspects of MG

2.1. Microgrid Structure

MGs are coordinated schemes that employ distributed energy resources (DERs) using a grid that can be linked or detached from the UG at the point of common coupling (PCC) (Figure 3). The PCC is the point where the power generation and loads are joined together. The following sections explore the components that establish an MG.

Figure 3. The layout of a microgrid (MG).

2.1.1. Distributed Generators (DGs)

An MG is a wise choice for incorporating various types of DGs because they can utilize several sources in different locations. DGs such as wind turbines, photovoltaics (PVs), biomass and fossil fuel-based generators and hydro-turbines act as small-scale power generators that can supply power to end-users. They significantly reduce emissions [9]. DGs can efficiently produce and deliver energy, while offering significant environmental benefits.

Figure 2. Flow diagram of the review process.
benefits. DGs include a controller to regulate frequency/voltage and active/reactive power to assure a successful and smooth connection with MGs [10].

2.1.2. Storage Systems

Energy storage systems (ESSs) are important components of MGs because they serve as standby power generators for RESs. ESSs store energy from local DGs when excessive energy is generated, or from the UG when the market price is low. They return energy to the grid during peak demand periods to reduce interruptions and maintain system stability. An ESS can significantly reduce the fluctuating effects of RESs, providing a cost-effective MG operation and better system efficiency. Moreover, it can improve other system characteristics, such as stability, PQ, power imbalance, reliability, and remote MG operation. Furthermore, ESSs can enhance transient and dynamic stabilities, voltage unbalance (VU), and frequency control to develop a dynamic power system. Several studies have presented extensive discussions of ESS operations in power systems [11–13].

2.1.3. Loads

MGs can deliver power to various types of loads, such as for residential or industrial use, which are typically classified as critical and non-critical loads to control and attain the expected operation of MGs [14]. This strategy prioritizes ensuring service to critical loads and enhances the reliability and PQ of particular loads. Critical loads are disconnected during grid faults using protective systems, and are then continuously operated using local generation (users’ own generation facility) [14].

2.2. Mode of Operation

MGs can operate in two modes, islanded and grid-tied modes [15]. In the following subsection, these MG operation approaches are discussed in detail.

2.2.1. Islanded Mode

MGs are typically linked to the UG through a PCC and are mostly tied to an electric power network at medium (or low) voltage levels. In the islanded mode, the MG is disconnected from the UG but can provide a consistent power supply to users, based on DG bids. ESS-integrated MGs increase the effectiveness and reliability of the power network, which in turn reduces the power fluctuations caused by RESs. In emergency cases, if the MG is disconnected from the UG owing to network faults, the MG may operate separately (in the islanded mode) with the support of DGs and the integration of battery ESSs (BESSs) to maintain power network reliability and stability [16]. The primary objective is to regulate the frequency and voltage of the network. Harmonization during the rejoining of the MG with the network is recovered using frequency discrepancies between the UG and MG in the islanded mode [9,17]. Figure 4 shows an MG system operating in the islanded mode, using a switch for changeover actions.

2.2.2. Grid-Tied Mode

In the grid-tied mode, MGs can deliver (or consume) energy to (or from) the UG, depending on the power network requirement. Adopting BESSs along with MGs significantly improves the system operation because they improve the reliability of the system [18]. BESSs can maintain frequency and voltage variations to keep them within tolerable ranges, to ensure the reliability of MGs. Usually, BESSs are employed along with RESs to facilitate standby generation, supply power to reduce the peak load demand during grid outages, and control voltage and frequency to stabilize the grid. BESSs are also used in the demand response (DR) approach in the grid-tied mode, to control the voltage and frequency of the power system. Several studies, exploring BESS sizing and best scheduling, the EMS approach, and the control of MGs in grid-tied schemes have been conducted to realize economic electricity generation [9,18,19]. Grid-tied MGs include a PCC and an intelligent bi-directional switch (Figure 5). The bi-directional switch manages the two-way connection...
of the MG to the main UG. The MG can take energy from the UG when it is needed, as well as transferring surplus power to the UG.

![Figure 4. Islanded mode of MG operation.](image)

**Figure 4.** Islanded mode of MG operation.

![Figure 5. Grid-tied mode of MG operation.](image)

**Figure 5.** Grid-tied mode of MG operation.

### 2.3. Classification of MGs

According to the operating method specified by the Consortium for Electric Reliability Technology Solutions [15], MGs are classified into three groups: alternating current MG (ACMG), direct current MG (DCMG), and hybrid AC–DC MG (Figure 6).

![Figure 6. Classification of MGs.](image)

**Figure 6.** Classification of MGs.

#### 2.3.1. Alternating Current MG (ACMG)

An ACMG is linked to the UG via a PCC, in which a switch controls the MG operating modes. A power electronic device is required for those DGs that produce a DC voltage, including ESSs, to convert it into an AC voltage that can be connected to an AC-bus system. Figure 7 represents an ACMG system connected to the UG via a PCC. An ACMG is
simple to install and connect to the traditional UG when implementing a reconfigurable system. The generators, storage devices, and user loads need to be compatible with the UG. The voltage transformation and regulation are easy because of the electrical transformers. Moreover, circuit protection and security schemes are mature for AC systems [14]. The main shortcoming of the ACMG technique is that it requires vast and complicated power electronic devices to integrate DGs with the UG, introducing a harmonic effect in the power network [20]. In addition, parameters such as voltage magnitude, frequency, and phase angle must be coordinated and harmonized with the existing UG. These requirements restrict the use of ACMGs with UGs. An ACMG usually requires more additional transformation stages than a DCMG [20].

2.3.2. Direct Current MG (DCMG)

The DCMG scheme can be efficiently integrated with DGs, as it mainly generates a DC voltage. ESSs and RESs both operate with a DC voltage. DCMG systems are typically attached to the UG through a PCC. In this technique, ESSs, PVs, electric vehicles (EVs), and DC loads are linked to the DC bus via DC–DC converters. AC loads, along with wind turbines and diesel generators, are attached to a DC bus through AC–DC converters. Figure 8 illustrates the structure of a DCMG system. The architecture of the DCMG system is much simpler than that of an ACMG system, as it does not require grid harmonization of DGs, harmonics, and reactive power flow, which improves the system efficiency [21]. However, the use of power electronic converters creates reliability problems and contributes to the ineffective power flow control from/to the distribution UG [14].
2.3.3. Hybrid AC–DC MG

This approach is a combination of ACMG and DCMG. In this architecture, the ACMG is directly linked to the PCC. However, the DCMG uses a two-way AC–DC converter to connect with the AC-bus system [22]. A control unit is required in each converter to ensure the reliability and effectiveness of the network. The control unit is situated between the UG and network buses (Figure 9). A bidirectional converter is employed to control and regulate the DC bus voltage and power flow between the AC and DC MG. The main advantage of hybrid MGs is that the DG units can be easily connected to the DC- or AC-bus because DGs do not require synchronization. Thus, the control is simple and reduces energy losses. However, the control schemes in MG have some problems, which are discussed in [23]. Table 1 gives a comparison between various MG operation schemes.

![Figure 9. Hybrid MG-based power system.](image)

Table 1. Comparison between MG operations.

| Type       | Conversion                                                                 | Merits                                                                                      | Demerits                                                                                      | Refs   |
|------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------|--------|
| ACMG       | DC loads require an AC–DC converter; AC loads can easily connect to the bus | Easy reconfiguration; easy voltage transformation and regulation                           | Requires vast and complicated power electronic devices to integrate DGs into the UG; difficult to synchronize the voltage magnitude, frequency, and phase angle with the existing UG | [14,15,20] |
| DCMG       | Requires a DC–DC converter and DC–AC inverter                                | Few converters are necessary; DC loads can easily connect to the bus; no synchronization required | Reconfiguration with the existing UG is complicated; difficult to produce an AC voltage; difficult to maintain a standardized voltage level | [14,21] |
| Hybrid MG  | A transformer is used on the AC side, and a DC–DC converter is used on the DC side | Both AC and DC loads can easily connect to the bus; less energy loss                      | Difficult to manage and control; complex architecture                                         | [22,23] |

3. Islanding Detection (ID)

MGs can operate in islanded or grid-tied mode, based on various approaches. An efficient islanding detection technique (IDT) is essential for achieving optimal MG operation. System reliability is a key priority in the islanding approach, whereas the main goal of the grid-tied approach is to achieve the best economic operation of MGs. Thus, identifying the operation state in real time is indispensable for maximizing the performance of MGs. Islanding may be subdivided into controllable and uncontrollable islanding [24]. Control-
itable islanding involves MGs consistently delivering power to fulfill the load while they are disconnected from the UG. Unplanned islanding is an undesirable situation caused by problems such as equipment failure, line-tripping, and human errors, with MGs being detached from the UG. This may occur infrequently and affect the safety of MG.

3.1. ID Standards and Test Indices

An MG should detect the failure of the grid connection and isolate itself from the power supply network within 2 s of the occurrence of unplanned islanding [25]. A reliable and efficient IDT is required for detection. Many ID standards have been prepared as instructions for researchers to develop and enhance IDTs. These standards incorporate IEEE Std.1547-2003, IEEE Std. 929-2000, UL 1741, IEC 62116, the Canadian C22.2, UK G83/2/3, Korean, German VDE0126-1-1, Japanese and AS4777.3-2005 [25–28]. Table 2 lists the standards for ID, giving its required detection time, quality factor, frequency, and voltage operating range. Rapid detection is a prerequisite for MGs to have sufficient time to operate the islanding approach, ensuring security and reliability. Islanding disconnection time is also imperative. The German VDE0126-1-1 standard has the strictest disconnection time limit, below 0.2 s [29]. Besides detection time, the quality factor ($Q_f$) is also important.

According to the IEEE929-2000 standard, $Q_f$ can be represented as shown in Equation (1). The selected $Q_f$ of 2.5 corresponds to a power factor (PF) of 0.37. As PF increases, $Q_f$ decreases. Therefore, the test requires that $Q_f \leq 2.5$ equates to lines with uncorrected PFs from 0.37 to unity, and appears to cover all reasonable distribution line configurations [29]. With the $Q_f$ at zero, where either capacitive or inductive loads are zero, the Japanese standard recommends introducing a rotating machinery load when the MG is investigated for anti-islanding. The machinery load is supposed to behave in such a way as to increase the $Q_f$. In addition to the $Q_f$, the voltage/frequency operation range also influences the ID capability. The Australian Standard AS4777.3-2005 and Japanese Standard require that frequency and voltage ranges are set by the manufacturer.

$$Q_f = \tan(\arccosine[PF])$$

(1)

| Standard          | Detection Time | Quality Factor | Frequency (Hz) | Voltage (p.u.) |
|-------------------|----------------|----------------|----------------|----------------|
| IEEE 1547         | $t < 2$ s      | 1              | $59.3 \leq f \leq 60.5$ | $0.88 \leq V \leq 1.1$ |
| IEEE 929-2000     | $t < 2$ s      | 2.5            | $59.3 \leq f \leq 60.5$ | $0.88 \leq V \leq 1.1$ |
| UL 1741           | $t < 2$ s      | 2.5            | $59.3 \leq f \leq 60.5$ | $0.88 \leq V \leq 1.1$ |
| IEC 62116         | $t < 2$ s      | 1              | $(f_o - 1.5) \leq f \leq (f_o + 1.5)$ | $0.85 \leq V \leq 1.15$ |
| VDE 0126-1-1      | $t < 0.2$s     | 2              | $47.5 \leq f \leq 50.5$ | $0.88 \leq V \leq 1.1$ |
| Canadian C22.2    | $t < 0.2$s     | 2.5            | $59.5 \leq f \leq 60.5$ | $0.88 \leq V \leq 1.06$ |
| UK G83/2 or       | $t < 0.5$s     | 0.5            | $47.5 \leq f \leq 51.5$ (Stage 1) | $0.87 \leq V \leq 1.1$ (Stage 1) |
| UK G83/3          | $t < 0.5$s     | 0.5            | $47 \leq f \leq 52$ (Stage 2) | $0.8 \leq V \leq 1.19$ (Stage 2) |
| Korean standard   | $t < 0.5$s     | 1              | $59.3 \leq f \leq 60$ | $0.88 \leq V \leq 1.1$ |
| AS4777.3-2005     | $t < 2$ s      | 1              | Setting value     | Setting value   |
| Japanese standard | Passive: $t < 0.5$ s | 0 (+ rotating machinery) | Setting value     | Setting value   |
|                   | Active: $0.5 \leq t < 1$ s | Setting value | Setting value     |

The performance of IDTs is determined by the accurate, effective, and timely detection of islanding. The test indices comprise the non-detection region (NDR), detection time, error detection (ED) ratio, PQ, effect on MG, and implementation cost.

3.1.1. Non-detection Region (NDR)

NDR is the region of an IDT in which islanding occurrences cannot be detected. NDR is an important factor for measuring the accuracy and capability of the IDT. NDR can be defined based on the voltage and frequency range, along with the active and reactive power imbalance and load parameter space [30].
• **Power Mismatch Space**

The frequency and voltage variations at the PCC are related to the power discrepancy between generation and load demand when the MG works in a scheduled mode. The power mismatches, $\Delta P$ and $\Delta Q$, will be zero if the DG power generation and load demand are equal [31]. $\Delta P$ and $\Delta Q$ can be obtained using Equations (2) and (3), respectively. The quality factor ($Q_f$) is described as the strength of resonance of the islanding test load, as shown in Equation (4). NDR is obtained using these equations (Figure 10) [32]. For $\Delta P$ and $\Delta Q$ in the shaded region, islanding is not detected. Another effective method was introduced in [33] to determine the NDRs for a typical frequency and voltage for synchronous-based DG. The approach is feasible for assessing NDR using a few analytical statements, without the need for time-consuming simulations.

$$\left(\frac{V}{V_{\text{max}}}\right)^2 - 1 \leq \frac{\Delta P}{P} \leq \left(\frac{V}{V_{\text{min}}}\right)^2 - 1$$  \hspace{1cm} (2) \\
$$Q_f \left(1 - \left(\frac{f}{f_{\text{min}}}\right)^2\right) \leq \frac{\Delta Q}{P} \leq Q_f \left(1 - \left(\frac{f}{f_{\text{max}}}\right)^2\right)$$  \hspace{1cm} (3) \\
$$Q_f = R\sqrt{C/L}$$  \hspace{1cm} (4)

where $V_{\text{max}}$ and $V_{\text{min}}$ are the maximum and minimum voltages permissible in MG; $f_{\text{max}}$ and $f_{\text{min}}$ are the maximum and minimum frequencies; $V$ and $P$ are the rated voltage and active power; $\Delta P$ and $\Delta Q$ are the active and reactive power mismatch, respectively; $Q_f$ is the quality factor; $R$, $L$, and $C$ are the load resistance, inductance, and capacitance, respectively.

![Figure 10. Schematic of NDR.](image)

• **Load Parameter Space**

NDR in the load parameter space can be represented as:

$$F_1(c_f, G, Q_f) < \Delta C_{\text{res}} < F_2(c_f, G, Q_f)$$  \hspace{1cm} (5)

where $c_f$, $G$, and $Q_f$ are the chopping fraction, acceleration gain, and quality factor, respectively.

In [31], the author used the $L \times C_{\text{res}}$ axis (inductance $\times$ resonate capacitance) to define NDR in the load parameter space. In this technique, the load resistance is determined by assuming a power match between the DG and load demand. In [34], an alternative method considering $Q \times f_r$ was employed to define NDR, where $f_r$ is the resonance frequency. The key advantage of this technique, compared with the previous technique, is that it does not require the use of various curves to analyze NDR with numerous resistive loads.

3.1.2. Detection Time

Detection time is the period between the MG’s disconnection from the UG to the moment of islanding detection by IDTs, and is given as:

$$\Delta T = T_{\text{IDT}} - T_{\text{trp}}$$  \hspace{1cm} (6)
where $\Delta T$ is the run-on time, $T_{IDT}$ is the time of islanding, and $T_{trp}$ is the time at which the MG disconnects from the UG.

3.1.3. Error Detection (ED) Ratio

The ED refers to a situation in which the IDT identifies incorrect islanding, although the MG is connected to the UG. The incorrect ID may happen because of load switching or various disturbances, which leads to the measurement tools surpassing their limit [35]. The ED ratio can be estimated as follows:

$$E_r = \frac{N_{ed}}{N_{ed} + N_{cd}}$$

where $E_r$ is the ED ratio, and $N_{ed}$ and $N_{cd}$ are the total numbers of ED and correct detection, respectively.

3.1.4. Power Quality (PQ)

Techniques that consider disturbance injection can considerably diminish NDR when identifying islanding. Nonetheless, it is necessary to introduce interference to deform the power output profile and degrade PQ. This is an important test parameter when selecting IDTs.

3.1.5. Effect on MG

Injecting disturbances in the system does not have any considerable impact when the DGs are attached to the UG. However, it considerably reduces PQ if the MG is detached from the UG. Therefore, IDTs with less impact on the MG are preferred.

3.1.6. Implementation Cost

Several IDTs incorporate improved and sophisticated hardware for improving operation. However, higher performance at a huge investment cost reduces its practical utilization. Therefore, an optimal balance should be maintained between performance and the investment cost in real-time applications.

3.2. Islanding Detection Techniques (IDTs)

IDTs are generally categorized as remote (central) and local (Figure 11). Local IDTs measure the parameters on the MG side. They are further subdivided into passive, active, and hybrid techniques [36]. Passive techniques directly monitor parameters such as current, voltage, phase, and frequency for ID. Active techniques purposefully introduce a noisy disturbance to check whether it affects the frequency, voltage, and other parameters of the system.

3.2.1. Local Techniques

The local techniques are classified into three groups. These are described in the following subsections.

- **Passive Techniques**

  These were the first techniques used for ID. The passive IDTs directly monitor parameters such as current, voltage, total harmonic distortion (THD), and frequency at the PCC to the UG. A threshold limit is defined for the parameters, and the outstripping of this predefined limit denotes islanding. The parameters significantly differ if the MGs are isolated. The protective relays sense the deviations and send a signal to trip the breaker switch. Figure 12 shows the basic block diagram of a passive IDT. Studies have introduced several passive IDTs, some of which are discussed below.

  1. Under/overvoltage (UOV) and under/over frequency (UOF): UOV/UOF is the oldest passive technique. It operates based on the setting of the allowable range of voltage and frequency. This technique is employed in all grid-tied inverters to measure
various abnormal conditions. Inverters stop the supply of power (both active and reactive power) if the frequency and voltage exceed the predefined limits at the PCC. In the MG, the power discrepancy between the generation and load demands at the PCC can be represented as follows:

\[ \Delta P = P_{\text{load}} - P_{\text{DG}} \]  
\[ \Delta Q = Q_{\text{load}} - Q_{\text{DG}} \]

where \( \Delta P \) and \( \Delta Q \) are the active and reactive power mismatch; \( P_{\text{load}} \) and \( Q_{\text{load}} \) are the active and reactive load; \( P_{\text{DG}} \) and \( Q_{\text{DG}} \) are the active and reactive DG power.

In the grid-tied mode, the UG adds \( \Delta P \) and \( \Delta Q \) to balance the active and reactive power. However, if islanding occurs, its frequency and voltage will drift until the active and reactive powers are balanced; thus, this technique detects islanding by measuring frequency and voltage variations.

Although this technique has no impact on PQ, its primary weaknesses are its extensive NDR and unpredictable detection time, which may exceed 2 s [37]. One method was proposed to minimize NDR by implementing an interface control in parallel to UOV and UOF [38]. Another method proposed decreasing the NDR by controlling the P–V and P–Q characteristics of constant-current-controlled inverters [36].

2. Harmonics measurement: this technique monitors the change in THD and primary harmonics (3rd, 5th, and 7th) at the PCC to identify MG isolation [39]. Under normal conditions, when the MG is connected to the UG, insignificant harmonics are introduced by loads because the grid impedance is small. When the MG operates in the islanding state, the inverters develop current harmonics, which are transferred to the load, and the transformer’s hysteresis effect further exacerbates harmonic distortions at the PCC. Thus, MG islanding can be easily identified [40].

The implementation of this technique is easy even when multiple DGs are connected to the same PCC. Conversely, high Q-factor detection using this technique is difficult, and detection limit selection is challenging because UG disturbance can easily induce false detection [36].

3. Phase Jump Detection (PJD): this technique is based on measuring the phase discrepancy between the output current and terminal voltage of the inverter, which typically occurs as a sudden “jump.” In normal MG operation, the inverter’s current and voltage will be harmonized at the PCC by modifying the phase-locked loop (PLL) required by the inverters. If isolation occurs, the local load and inverter are separated from the UG. The PJD system checks variations in the phase angle to identify islanding [31]. This approach is simple to implement, does not distort the inverter PQ, and can be used in multi-inverter systems [41].

The main limitation of this technique is in the setting of detection limits because of the load-switching effects. It is challenging to detect islanding using this technique if the loads do not generate a large enough phase error. Thus, PJD is useful only for MGs that evince nearly constant load switching and a large phase angle.

4. Rate of Change in Frequency (RCF): The frequency will change if the MG disconnects from the UG. When the frequency surpasses a set limit, the inverters shut down, and islanding is identified. RCF is evaluated over a few cycles [42]. RCF is more responsive, and its detection time (24 ms) is less than that of UOV/UOF [43]. Any distortion generated by load variations could lead to frequency deviations in ID. Nonetheless, when severe frequency deviations occur, the detection time can be in fewer than five revolutions [44]. The main shortcoming of RCF is that it is very responsive to load fluctuation and switching (even a small disturbance can change the frequency), which may affect ID. Moreover, the selection of the detection limit is challenging. This technique is unable to discriminate between islanding and load variations as the cause of frequency change [45]. Thus, RCF is not suitable for loads with high variations.
5. Rate of Change in Power (RCP): This technique monitors DG power output changes because the disconnection from the grid causes load changes. When the MG is islanded, the RCP output will be higher than that of the MG in the grid-tied mode, even when the load change rate is equal in both cases. Thus, the power changes are monitored for a few test cycles. The MG will be isolated from the UG if the combined changes in the test cycles surpass the set detection limit. The rate of change in the reactive power approach was proposed in [46] to detect the islanding of synchronous generator-based DGs.

The usual detection time of RCP is approximately 24–26 ms [43]. In comparison with UOF, the detection time is not affected by such small power discrepancies. This technique can also immediately identify uncoordinated reclosing of the UG supply to the MG to ensure the reliable functioning of the electric power network. However, this technique has an NDR, even under power balance conditions.

6. Voltage Unbalance (VU): When the MG disconnects from the UG, the VU of DG changes because of the change in the network topology. If the unbalance in the three-phase DG output voltage surpasses the allowable limit, this is considered islanding [47]. The VU deviation is monitored and compared under normal and steady-state loading conditions, and any unexpected VU is identified as MG islanding. The single-cycle average of VU and VU deviation was investigated every 1/4 cycles (4.17 ms) in [48]. Recently, single-cycle control-based inverters to detect islanding were proposed in [49], where simulation results showed that this technique could work effectively with less NDR.

Passive detection techniques are cost-effective, easy to implement, and have short detection times. Thus, these techniques can handle most of the instabilities that occur in the UG. Nevertheless, the main shortcoming of passive IDTs is the large NDR, which hampers the identification of the correct MG operating state. In addition, the load affects islanding detection in these techniques. These shortcomings could be resolved using active IDTs, which are discussed in the following section. Table 3 gives a comparison between various passive IDTs, highlighting their benefits and limitations.

Table 3. Comparison of passive islanding techniques.

| IDT     | NDR                        | Detection Speed | Error Detection Rate | Implementation and Speed | Improvement                                                                 | Ref       |
|---------|---------------------------|-----------------|----------------------|--------------------------|-----------------------------------------------------------------------------|-----------|
| UOV/UOF| Large                     | 4 ms to 2 s     | -                    | Easy but reaction time is variable                                       | Additional parameter is implemented with the UOV/UOF [36–38]               |
| THD     | Large with a high Q factor| 45 ms           | High                 | Easy but challenging to define a threshold                               | Complicated implementation, challenging to define a threshold Controlled using a PLL [36,40] |
| PJD     | -                         | 10 to 20 ms     | High                 | -                         | Complicated implementation, challenging to define a threshold Controlled using a PLL [41] |
| RCF     | small                     | 24 ms           | High                 | Easy but selection of threshold is difficult                             | -                                                   | [43,45]   |
| RCP     | Smaller than UOV/UOF      | 24 to 26 ms     | -                    | More complicated than UOV/UOF                                           | Combining VU and THD to enhance the performance [43]                        |
| VU      | -                         | 53 ms           | Low                  | Easy for a three-phase system                                           |                                                                                   | [47,48]   |
Active Techniques

Active IDTs are implemented by injecting a minor disturbance, as shown in Figure 13, into the UG to determine whether the MG is in the islanding state (Figure 13). The disturbance is injected at specific intervals. Numerous active IDTs have been introduced in the literature; some of them are discussed in the following subsections.

1. Impedance Measurement (IM): this technique involves varying the current amplitude of the inverter. When the MG is separated from the UG, the voltage magnitude changes because of the change in the current’s magnitude, which causes an impedance variation that can be employed for ID [40]. However, in an active direct technique, a shunt inductor is temporarily attached to a supply voltage. The supply voltage reduction and short-circuit current approaches are utilized to determine the power system source impedance [36].
The IM-based ID time is approximately 0.77–0.95 s [29], and its NDR is very small for individual DG systems, which is its main advantage. However, this technique has many limitations, including its low detection performance for multi-inverter arrangements, except when all inverters are working simultaneously. Moreover, it is difficult to define the impedance base limit because IM requires a precise UG impedance value. Thus, the practical implementation of this technique represents a challenge.

2. Sliding Mode Frequency Shift (SMFS): this technique employs positive feedback to vary the phase at the PCC, followed by using the temporary frequency to identify islanding. The phase angle of the inverters can be defined as follows:

$$\theta = \theta_x \sin \left( \frac{\pi}{2} \frac{f_{m-1} - f_y}{f_x - f_y} \right)$$ (10)

where $\theta_x$ is the maximum phase angle at the frequency $f_x$, and $f_y$ and $f_{m-1}$ are the rated and previous cycle frequency, respectively.

When the MG is operating under normal conditions, the phase angle between the PCC voltage and inverter current is maintained at close to zero. The phase angle of the frequency and load may change when the MG is detached from the UG. Thus, islanding can be detected if the frequency deviation surpasses the set limit [50]. The detection time of SMFS is approximately 0.4 s [34]. The main benefits of SMFS are that its implementation is easy, and it has a smaller NDR than other active techniques. However, this technique reduces the grid PQ and transient stability. These problems are common for all techniques that use positive feedback. This could be solved by including an extra phase shift, called the enhanced-SMFS [50].

3. Active Frequency Drift (AFD): similar to SMFS, this technique employs positive feedback to change the frequency of the inverter current. In a grid-tied mode, the PCC voltage and frequency will not change, owing to the steadiness of the UG. When grid separation occurs, the voltage crosses zero earlier than expected, thus creating a phase discrepancy between the inverter’s current and voltage. This induces the inverter to drift the frequency of the current to cancel the phase discrepancy. The drift frequency outstrips the set limit, and islanding can be identified [47]. The advantages of AFD are that its implementation is simple, and it has a small NDR. Notably, no NDR is present in resistive loads within a sensing period of 2 s [29]. However, this technique is unable to detect islanding for multiple inverters because of various deviations in the frequency bias of the inverters [51]. The PQ of the inverter output deteriorates more rapidly with the increase in the distortions in the injected current. Load parameters have a significant effect on this technique. The islanding sensing time and NDR increase with higher Q values if the load is not resistive. Thus, AFD is only suitable for an ID of MGs comprising resistive loads and a single inverter. The Fourier series coefficients and RMS value of the current waveform are used to improve traditional AFD. This approach can decrease THD by approximately 30% of the current waveform. Hence, the technique can rapidly identify islanding with a reduced NDR. The performance of the traditional approach can be significantly enhanced by using AFD with positive feedback (AFDPF) [52].

4. Sandia Frequency Shift (SFS): this technique, typically called AFDPF, is a modification of AFD that uses positive feedback for ID. At PCC, this technique tries to alter the voltage frequency when attached to the UG, but the UG prohibits this. When detachment from the UG occurs, the chopping coefficient increases with the frequency increase at PCC. This results in an increase in the inverter frequency. This frequency shift enables efficient ID. The ID time here is approximately 0.5 s.

The implementation of this approach is simple, and its NDR is small compared with those of other active IDTs. SFS is used in conjunction with the Sandia voltage shift (SVS)-related islanding technique, which is a very efficient approach [53]. Nonethe-
less, SFS significantly affects the PQ and the system stability, which may lead to adverse behavior in the system response. Furthermore, positive feedback introduces harmonics and noise [54].

5. Frequency Jump (FJ): this is another modified form of AFD, based on varying the voltage frequency to identify islanding. When the MG is detached from the UG, islanding could be determined by an alteration in the voltage frequency [29,31]. FJ is efficient in discovering MG isolation with a single inverter. However, as is similar to AFD, the identification efficiency decreases when multiple inverters are connected in parallel.

6. Sandia Voltage Shift (SVS): this technique is analogous to SFS. By employing positive feedback in the voltage amplitude at PCC, the inverter modifies its power and current. In the grid-tied mode, the voltage amplitude is unaffected by the power change, whereas, without connecting with the UG, the power variations stimulate the voltage drift to identify islanding [40]. The SVS scheme is simple to implement and operate, and its performance is similar to that of SFS. The main disadvantage of SVS is that it somewhat degrades PQ. In this technique, the inverter operation efficiency is reduced because of the frequent changes in the inverter’s output power [40,55].

7. Negative-Sequence Current (NSC) Injection: this technique involves injecting NSC into a voltage source converter and measuring the voltage at the PCC, to identify MG isolation. When the MG is attached to the UG, the injected NSC passes through the UG without affecting the voltage at the PCC. However, the injected NSC passes through the load and leads to an imbalance in the PCC voltage when the MG is detached from the UG, causing the voltage to exceed the threshold. This technique can identify islanding within 60 ms, which is an extremely short detection time compared with other active techniques [56]. This technique offers the advantages of not having NDR and being unresponsive to load variation.

The above studies reveal that active techniques offer higher reliability, a smaller NDR, and better ID efficiency than passive techniques. However, the critical shortcoming of active IDTs is the disturbance in the power network, which significantly degrades PQ. The islanding identification time is longer because additional time is required to respond to the disturbance. Table 4 gives a comparison between various active IDTs.

| IDTs       | NDR                | Detection Speed | Error Detection (ED) Rate | Implementation and Speed | Weakness                                         | Ref.          |
|------------|--------------------|----------------|---------------------------|--------------------------|-------------------------------------------------|--------------|
| IM         | NDR small for a single system | 0.77 to 0.95 s | -                         | Easy and fast            | Performance declines with multiple-inverter systems | [29,36,40]   |
| SMFS       | NDR smaller than AFD | Approx. 0.4 s  | Low                       | Easy and medium          | PQ and transient stability problems             | [34,50]      |
| AFD        | NDR increases with higher Q | Approx. 2 s    | High                      | Easy and medium          | Performance declines with multiple-inverter systems | [29,47,52]   |
| SFS        | Smallest NDR       | Approx. 0.5 s  | Low                       | Complex but fast         | PQ and transient stability problems             | [31,53]      |
| SVS        | Smaller than UOV/UOF | Low           | Medium and fast           | -                        | Degrades PQ                                      | [40]         |
| NSC injection | No NDR            | 60 ms         | Low                       | -                        | Degrades PQ; less stable operation              | [56]         |
Hybrid Techniques

This technique combines passive and active IDTs as the main and subordinate techniques, respectively, (Figure 14) for enhancing the detection accuracy. Some hybrid techniques are briefly discussed in the following subsections.

1. Voltage Unbalance and Frequency Set Point: a hybrid technique that employs positive feedback, VU, and THD techniques was proposed in [57]. The hybridization eliminates the individual shortcomings of both approaches. The three-phase voltages are constantly measured at the DG output terminal while the VU is calculated. Because VU is more responsive to system disturbances, VU is calculated for every MG, rather than THD. When any disturbance occurs in MG, a high VU peak is generated. This approach can effectively distinguish between the islanding state and load switching. The detection time of this hybrid technique is ~0.21 s [57].

2. Voltage and Real Power Shift: this method uses voltage variation (passive IDT) and actual power shift (active IDT) to eliminate the individual drawbacks in determining the MG operating state [58]. Using this technique, islanding can be identified with a multi-inverter-based MG working at a PF of unity. The active IDT is employed in the system network if the passive IDT fails to recognize the MG isolation. This approach can only alter the real power of the MG at a PF of unity.

3. Voltage Fluctuation Injection: this approach is based on the addition of voltage variation. Here, a passive IDT (RCF/RCV) and an active IDT (correction factor) are combined as a standby to obtain improved efficiency. This method uses digital signal processing to determine the correction factor, RCF, and RCV to precisely distinguish the types of disturbances [36]. In [59], RCF is applied as a safety system, while dynamic power fluctuation and reserve VAR detection are used as a standby safety system during islanding state identification. The NDR decreased for ID when RCF was employed with an active technique. This technique can determine MG islanding in 0.21 s [60].

4. Hybrid SFS and Q–f Approach: in this approach, SFS (active IDT) and the Q–f droop curve (passive IDT) are combined in order to detect islanding. The optimal gain is obtained by employing an optimization technique to reduce the limitation of SFS and minimize NDR. Next, the Q–f droop curve is utilized to increase the effectiveness of ID [61].

5. Combining VU with SFS and SVS: this approach can decrease the adverse effects on the power system transient response compared with using SFS and SVS techniques alone [57]. Unlike the VU approach, this technique can easily segregate the load switching and islanding states with no false detection.

Hybrid techniques can reduce NDR and enhance detection accuracy. Furthermore, these methods do not significantly affect PQ. However, they do increase the system complexity. Table 5 gives a comparison between different hybrid techniques.
Figure 14. Basic block diagram of hybrid IDTs (black color rectangle represents passive technique and red color rectangle represents active technique).

Table 5. Comparison of Hybrid IDTs.

| IDTs                        | NDR  | ED Rate | Implementation and Speed | Weakness                                      | Ref  |
|-----------------------------|------|---------|--------------------------|-----------------------------------------------|------|
| VU and frequency set point  | Small| Low     | Complex and fast         | Slightly degrades PQ; slow for ID              | [57] |
| Voltage and real power shift| -    | Low     | Complex and moderately fast| Only effective at unity PF                    | [58] |
| Voltage fluctuation injection| NDR is reduced when RCF is employed with an active technique| Low | Complex and moderately fast | Only useful in a complicated system | [36,59] |
| Hybrid SFS and Q-f approach | Small| Low     | Complex and moderately fast| Needs an additional tool to calculate the optimal gain | [61] |
| VU with SFS and SVS         | Small| None    | Complex but fast         | Only useful in a complicated system           | [57] |

3.2.2. Remote IDTs

The remote IDTs are categorized into two groups. These are described in the following subsections.

- Communication Based Techniques

Communication based IDTs depend on the information transfer between the MG and UG. They use communication frameworks and signal-processing approaches similar to those used for ID. Under normal conditions, the transmitter frequently sends a signal to the receiver. However, when islanding occurs, the communication breaks and the receiver does not receive any signal. Figure 15 shows the working principle of communication based IDTs.

Figure 15. Working principle of communication based IDTs.
1. Power Line Carrier Communication (PLCC)

In this technique, a transmitter is installed at the grid side and continuously sends a signal to a receiver installed at the MG side through the power line. If the PLCC signal is cut off, it implies that the MG is disconnected [62]. The PLCC signal duration is modeled through four successive cycles. MG isolation can be identified if the signal is interrupted in three consecutive cycles [63]. This technique does not influence PQ because it has a very small to no NDR. It also has no impact on the grid’s transient response. This technique is very efficient for multiple-inverter systems; however, it requires massive investment because of the expensive transmitters. Therefore, PLCC is uneconomical for low-density DG systems.

2. Signal Generated by Disconnection (SGD)

This technique is analogous to PLCC. It can identify islanding by monitoring the signal transmission status between the MG inverters and the UG. If the receiver fails to receive a signal for a predefined period, the MG will ultimately be tripped [64]. The main difference between the two techniques is that in SGD, communication is realized through telephone lines, microwaves, and other technologies [29]. SGD has no NDR, and it provides supplementary control to the MG through the UG, communicating between the MG and other UG sources. However, SGD needs a large investment because it requires communication wiring and communication protocols for the telephone line, as well as repeaters for signal transmission through microwaves.

3. Supervisory Control and Data Acquisition (SCADA)

This technique is based on communication between the MG and UG, via transfer-trip-detection schemes, to instantaneously monitor breakers. The status of circuit breakers is sent to the MG through the SCADA system [40]. This technique can regulate the MG, but it is comparatively slow in determining islanding. In addition, it requires complicated installation and verification; thus, it is uneconomical for small-scale systems.

The advantages of the remote techniques are that they have no NDR, show no deterioration in PQ, and are effective for multi-DG systems. However, they require additional instruments for establishing a communication network between the UG and MG, which increases the cost of the system. Table 6 summarizes the types of remote IDTs.

Table 6. Summary of communication-based IDTs.

| Techniques   | Advantages                                      | Disadvantages                        | Improvement                                      | Ref.     |
|--------------|------------------------------------------------|--------------------------------------|--------------------------------------------------|----------|
| PLCC         | Suitable for multi-inverter systems             | High cost of implementation          | -                                                | [62,63]  |
|              | no NDR; no effect on UG transient response      |                                      |                                                  |          |
| SGD          | Easy to implement; no NDR                       | Expensive                            | Need advanced communication to transfer signals; | [29]     |
| SCADA        | Communicates with all DGs; additional control of DG | Complicated; costly process;         | Direct transfer trip may escape MG isolation     | [40]     |

- Intelligent Techniques

Intelligent IDTs are related to communication techniques, but they do not require a threshold selection. The most common intelligent IDTs that are combined with signal-processing approaches include artificial neural networks (ANNs), probabilistic neural networks (PNNs), decision trees (DTs), support vector machines (SVMs), and fuzzy logics (FLs). In these techniques, the signal-processing unit extracts features from the signals and feeds them to the classifier for ID (Figure 16).
1. Artificial Neural Network (ANN)-based Technique

This technique has significant features that are utilized to monitor variations in the power system parameters. This technique involves using a computational framework resembling a biological system. It implements a mathematical scheme utilizing neural networks (NNs) similar to those in a biological brain [65], which store all information and data. An ANN-based IDT with multi-inverters was used in [66] to identify islanding, and it provided high accuracy and adequate system operation. This approach was also employed in [59,67] for ID. In [68], the measured parameters at the PCC were established using Fourier transform to obtain the second harmonic. The harmonic components were employed for the training of the ANN. The ANN-based approach is useful for detecting the islanding state; however, the feature choice and processing time of DGs in the MG require further investigations.

2. Probabilistic Neural Network (PNN)-based Technique

PNN is another classification approach that utilizes a Bayesian classifier. PNN overcomes the shortcomings associated with ANN, such as the computational burden and vulnerability to incorrect optima. PNN is generally employed in conventional pattern-recognition applications. It involves four stages: input, pattern, summation, and output [69]. Each stage executes its function for classifying the features without using any learning process. A PNN with several parameters was used in [70] for ID, and the simulation results proved that this approach is more effective for identifying the islanding state compared with other approaches. In [60], a PNN associated with the phase-space approach used an extracting feature to classify islanding states.

3. Decision Tree (DT)-based Technique

A DT is another classification approach used to identify the islanding state. The DT approach was used along with the wavelet packet transform (WPT) and the discrete wavelet transform (DWT) in [71] and [72], respectively. In these studies, the measured signals (voltage or current) for multiple DGs were provided to either the DWT or WPT for feature extraction, and the DT classifier was used to detect islanding states. DT can detect islanding with more than 99% accuracy. Induction and synchronous DGs have been studied [73] considering the noise effects, and the accuracy was approximately 96%. A DT-based IDT considering transient-state signals was introduced in [74]. Based on the simulation outcomes, the proposed technique achieved a classification accuracy of ~99%. A universal IDT was proposed in [75], in which several classification approaches incorporating DT were employed for ID events. In [36], the DT approach was modified and employed for hardware implementation, where a band pass filter replaced the function of the DWT.

4. Support Vector Machine (SVM)-based Technique

SVM is a dynamic classification scheme that specifies the decision boundary to segregate the data required for training [76]. The SVM classifier, including an autoregressive model, was introduced in [77] to extract the features of the current and voltage signals measured at the PCC. The proposed IDT yielded high classification accuracy with a shorter detection time. Moreover, an SVM approach for ID was proposed in [78,79]. The same method was applied to discriminate islanding from grid faults in a MATLAB/Simulink

Figure 16. Basic block diagram of intelligent IDTs.
environment [78]. An extensive study of the utilization of SVM, including S-transform, H-transform, mathematical morphology, and time–time transform for ID, was presented in [80]. SVM, combined with a mathematical morphology approach, demonstrated the highest accuracy (more than 98%). Nonetheless, SVM is less effective in practical applications because it involves a high computational burden, owing to data training and algorithm complexity.

5. Fuzzy Logic (FL)-based Technique

FL can be used as a classifier for detecting the islanding state. A fuzzy-based multi-criteria approach was introduced in [81] for ID. It monitors the changes in voltage, RCF, and RCP at the PCC, and islanding is identified using FL rules. The study in [82] combines fuzzy membership functions and rule-based (RB) schemes to enhance the fuzzy systems. This method is convenient for real-time ID. A fuzzy-RB classifier was proposed in [83] and [84], in which a DT sets the classification boundaries. The fuzzy membership functions and rules were developed with the boundaries to detect islanding. However, FL classifiers are extremely hypothetical, owing to different class combinations. Furthermore, FL-based techniques are more responsive to noisy data because of the repeated generation of rules [85].

Traditional techniques can effectively detect islanding but their performances degrade as the system complexity increases. However, intelligent approaches can simultaneously control multiple parameters and increase the robustness of the system. The use of intelligent techniques is increasing because of their low ID time and high accuracy. Figure 17 shows the proportion of research articles on different IDTs. Table 7 summarizes the types and features of intelligent IDTs.

![Figure 17. The proportion of research articles on different IDTs.](image)

| Classifier | Effectiveness of the Classifier | Weakness of the Classifier | Ref. |
|------------|--------------------------------|---------------------------|------|
| ANN        | Easy implementation            | Generally, needs to train the classifier | [65,66] |
| PNN        | Computational ease             | Effective for conventional pattern recognition | [69,70] |
| DT         | Quick training                 | Inconvenient for un-correlated variables | [72–74] |
| SVM        | Reduce training error          | Selection of parameters is difficult | [77,79] |
| FL         | Easy implementation            | Not robust                | [82,85] |

The comparison between various IDTs is shown in Table 8. It can be interpreted that none of the IDTs is accurate, as each technique has its own advantages and disadvantages. Figure 17 shows the proportion of research articles on different IDTs.
Table 8. Summary of various IDTs.

| IDT                      | Advantages                                      | Disadvantages                                      | Improvement                                                                 |
|--------------------------|-------------------------------------------------|----------------------------------------------------|-----------------------------------------------------------------------------|
| Passive technique        | No impact on PQ;                                | NDR is large; ED rate is higher than active technique | An improved passive technique considering the voltage/frequency behavior of the load and adaptively threshold can significantly reduce the NDR [86]. |
| Active technique         | NDR is small; ED rate is less                   | Deteriorates PQ                                    | A modified reactive power control approach can detect ID with negligible NDR. This method does not deteriorate PQ [87]. |
| Hybrid technique         | NDR is very small; ED rate is low               | Slightly deteriorates PQ; Only effective for a complicated system | A hybrid converter-based ID can achieve zero-NDR and does not degrade PQ [88]. |
| Communication based technique | No NDR; No impact on PQ; ED can be eliminated | Need a large amount of investment; Not economical for the small system | Various devices like smart meters, phasor measurement unit can be applied for ID. This can significantly reduce the implementation time and cost making it practical and economically viable. |
| Intelligent technique    | Easy implementation; No threshold selection is required | Need to train classifier; Parameter selection is difficult; Large computational burden | Advanced digital signal processing methods combined with a learning algorithm can be an effective tool for ID [89]. |

4. MG Energy Management System (EMS)

The EMS performs several functions, such as monitoring, analyzing, and predicting the DER power generation, energy, and ancillary market prices, load consumption, and meteorological conditions (Figure 18). These functions enable the EMS to obtain the optimal operation of MG while satisfying all constraints. Figure 19 shows the EMS for coordinated MG systems. In this MG structure, each MG EMS controls the power of its own MG. The surplus power from an MG is stored in the ESS or is delivered either to the distribution system or an adjoining MG through the coordination of the EMS. Similarly, the power shortage of the MG is acquired either from the UG or an adjoining MG under the coordination of the EMS. Thus, the EMS maintains an uninterrupted power supply throughout the entire system to stabilize it and maintain economical operation.

Figure 18. MG EMS functions.
4.1. Classification of EMS

The supervisory control scheme of an MG EMS may be divided into three categories: centralized, decentralized, and hybrid.

4.1.1. Centralized EMS

In the centralized approach, the central controller gathers all information, including DER generation status, consumers’ energy consumption status, meteorological data, and cost function. The principal objective of a centralized EMS is to maintain the energy equilibrium of the entire power network [90]. This approach mainly focuses on increasing reliability and cutting down costs. In addition, it efficiently deals with the external EMS (Figure 20). In Figure 20, the solid blue and black lines show a communication link and the power flow in the system, respectively. In the centralized model, only one optimization is performed by the EMS, while MGs are connected to the UG via a shared bus. The centralized EMS approach is suitable for the optimization of single-owner-based and standalone MGs. Central controller-based EMSs have been proposed and analyzed for AC, DC, and hybrid MGs in [91–93].
4.1.2. Decentralized EMS

In the decentralized EMS approach, each MG acts as an independent system and applies a local EMS to increase its benefits. Figure 21 shows a decentralized EMS scheme. Each MG can independently trade power with the UG. In some situations, the local EMSs can coordinate with adjoining MGs to share the surplus power [94]. Multiagent systems (MASs) are generally used for optimizing decentralized EMSs [90,95]. Decentralized EMSs are suitable for grid-tied MGs composed of numerous fast-changing DGs with multiple ownerships [94].

Figure 21. Decentralized EMS scheme.

4.1.3. Hybrid EMS

Hybrid EMSs have emerged to overcome the shortcomings of the centralized and decentralized EMS and to utilize the benefits of individual EMS [94,96–98]. In the hybrid approach, every local EMS optimizes the local sources only, and it notifies the central EMS about the extra amount/shortage of energy (Figure 22). The central EMS then controls the entire system resources and facilitates an energy interchange between MGs. Hybrid EMS-based strategies have been introduced in [97,98]. Table 9 lists the advantages and disadvantages of various EMS systems.

Figure 22. Hybrid EMS scheme.
Table 9. Advantages and Disadvantages of EMSs.

| EMS       | Advantages                                                                 | Disadvantages                                                                 | Ref       |
|-----------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------------|-----------|
| Centralized | Maintains the energy balance of the entire network; efficiently utilizes each MG component; low operating cost; simple implementation; trading is cost-effective | Massive communication structure is required; computational burden; unable to protect consumer privacy; entire system’s validation is required even for a single modification | [90–93]   |
| Decentralized | Protects consumer privacy; computational burden is distributed; flexible for plug-and-play functionality | Excessive power trading in the grid-tied mode; high operating cost; less resilient in the islanded mode | [90,94,95] |
| Hybrid | Protects consumer privacy; computational burden is distributed; flexible for plug-and-play functionality; more flexible than a centralized approach; lower operating cost than the decentralized approach | Only useful for MGs connected in parallel; cannot ensure consumer privacy; less resilient with disconnected MGs; MGs may operate autonomously if the central approach is compromised | [94,96–98] |

4.2. EMS-Based on Optimization Techniques

Optimization techniques optimize a given objective function by seeking the optimal parameter(s) from the basic parameter(s). These are classified into traditional mathematical and computer-based intelligent optimization methods. The traditional approaches (direct and gradient-based) apply a deterministic method to solve the optimization problems. The drawback of these approaches is that optimization turns into a more complex problem with a large search-area size [99]. Computational intelligence (gradient-free) approaches have been widely employed to handle such convoluted problems in various fields because of their high applicability, low time consumption, simplicity, and global prospect. Intelligent approaches can be categorized into heuristic and metaheuristic approaches. The metaheuristic approaches can be further classified into swarm-, evolutionary-, and physics-based methods [100].

4.2.1. Traditional Mathematical Optimization Approaches

Gradient-based methods utilize the theory of gradient/derivation knowledge to identify the best solution. These methods usually employ a double-step iterative process to determine the best solution. The initial step is to find the search path, depending on the gradient knowledge, and the next step is to move in the well-defined path until new instructions are received. This double-step process can be mathematically represented as follows:

\[ x_{k+1} = x_k + \alpha_k D_k \]  

where \( \alpha_k \) is the step size and \( D_k \) is the direction vector.

Linear programming is a technique to determine the optimal solution of a linear fitness function, taking into consideration the linear equality and inequality constraints. Nonlinear programming determines the solution of a nonlinear fitness function, in response to inequality constraints. Integer programming is a numerical optimization approach, in which some or all variables are specified to be integers. When some selection variables are non-discrete, the problem is recognized as a mixed-integer problem.
Dynamic programming is both a numerical optimization and a computational intelligence approach. It uses a specific search policy for the multi-layer decision process, which involves dividing the original problem into sub-problems. Stochastic programming involves numerical computing; however, the fitness function and constraints rely on problem variables and a random variable.

4.2.2. Computer Intelligent Optimization Approaches

- Particle Swarm Optimization (PSO)

PSO is a multiagent optimization technique proposed by Kennedy and Eberhart [101]. PSO uses diverse particle searching to obtain a globally optimal solution. The optimal information for each particle is stored in the particle memory (pbest) and the optimal global particle obtained among all particles is acknowledged as the global optimal particle (gbest). The velocity ($v_j^l$) and position ($x_j^l$) of each individual particle are renewed after every iteration as follows:

$$v_{j}^{l+1} = \omega v_{j}^{l} + m_1 r_1 (pbest_{j} - x_{j}^{l}) + m_2 r_2 (gbest_{j} - x_{j}^{l})$$

$$x_{j}^{l+1} = x_{j}^{l} + v_{j}^{l+1}$$

where $l$ is the number of iterations, $\omega$ is the inertia weight parameter, $m_1$ and $m_2$ are the user-specified constants, and $r_1$ and $r_2$ are the evenly distributed random numbers between 0 and 1. Figure 23 shows the elementary flow diagram of PSO. The main drawbacks of PSO are the premature convergence and the high risk of trapping in local optima.

- Genetic algorithm (GA)

A GA is a global optimization approach, influenced by Darwin’s theory of transformation [102]. This approach adopts the strategy of natural selection, in which the best entities are selected to produce offspring for the next generation. The offspring have the parents’ characteristics and incorporate them into the next generation. The offspring will be stronger and better. In addition, their survival chances increase with better parents. This process progresses until the optimal fitness value is obtained. Figure 24 illustrates an elementary flow diagram of a GA.
4.3. EMS Considering Conventional Techniques
4.3.1. Linear and Nonlinear Programming (LP/NLP) Techniques

The linear programming (LP)-based optimization model was proposed in [103] to identify the best operation of MGs. The authors suggested a power trading-, uninterrupted run-, and an on/off control-based MG EMS. The power trading is conducted through the UG, and a fuel cell is used for an uninterrupted power supply. The switching (on/off) approach is regulated using mixed-integer linear programming (MILP) that determines the best utilization of MG with the switching status of the UG, ESS, and fuel cell. In addition, the sizing of ESS is conducted based on operational demands. The MILP-dependent optimal model was introduced in [104] to determine the energy consumption schedule. The DR approach for controlling the fluctuation effects of RESs and minimizing peak consumption was also presented. HOMER simulation software was employed for optimal sizing of the MG. The linear fuel-utilization pattern of the diesel generator was employed as the fitness function, and a rain flow counting technique-based EMS was proposed as a trade-off between the running and capital costs of the MG [105]. The performance of the suggested EMS model was practically verified. Another MILP-based EMS was proposed in [106] to achieve energy trading for home-based MGs. The radial NN technique was used to predict the RES’s output power. The authors presented the advantages of using thermal storage and showed the unfeasibility of integrating battery storage in the residential network, owing to huge investment and replacement costs. An optimal EMS-based operating cost reduction model was introduced in [107] for residential MGs, which considered the energy trading cost, EV battery wear cost, and load-shedding penalty cost. A similar study investigated a profit-maximization EMS method that used the DR approach, combined with UG peak-shaving operation [108]. The IEEE 14-bus test network was employed to evaluate the efficiency of the suggested MILP-based MG approach, using commercial CPLEX software. Similarly, CPLEX software was used in [109] for an MILP-based nested EMS to minimize the operating cost of networked MGs and maximize reliability in the standalone mode. Hybrid AC–DC MGs were used to determine the performance of the suggested approach. The authors in [110] proposed a security- and privacy-controlled EMS for a three-phase home-based MG. The nonlinear optimization framework was introduced to reduce the MG running cost, taking into consideration the load-shedding penalty cost. The network blackouts were incorporated as a constraint to ensure the effectiveness of MG. The proposed approach was transformed into an MILP model, whose performance was evaluated by comparing it with the three-phase nonlinearity-based power flow approach. An MINLP-based EMS model was proposed in [111,112] to determine the optimal operation of an islanded MG. The MINLP approach introduced in [111] was split into NLP-based optimal power flow and MILP-based unit commitment models. The proposed optimization technique minimized the fuel and operating costs of traditional generations (TGs). In [112], the operating cost of TGs was incorporated as a fitness function, and the DR model was used to obtain the best operation of an isolated MG.

EMS has been extensively used to achieve the optimal operation of grid-tied MGs [113,114]. In [113], a centralized energy management structure of a grid-tied MG was developed. Two plans were proposed to regulate the price bids for MG integration in the electricity market. The purpose of the former approach is to reduce the operating cost of MGs, whereas the latter approach targets increasing revenue through energy-sharing with the UG. Both optimization problems were solved using sequential quadratic programming. A strategic EMS of a grid-tied MG, considering voltage security as a constraint, was proposed in [114]. The proposed model reduced the MG functioning cost using an improved gradient-descent-based technique, in which the backward–forward sweep method resolved the power flow problem. In addition, the consumer savings and profits, load leveling, and power network losses were considered in the objective function. Another study proposed a resilient EMS called ResEMS, which uses the reserve power procurement approach to run the MG in an isolated mode after disconnection from the UG due to manmade or natural disturbances [115]. The studied MG comprised a few PV cells, BESSs, and diesel generators.
The study aimed to reduce the electricity exchange and generation costs using the MILP algorithm. However, the authors did not employ a forecasting technique to predict the uncertainty in the PV generation, which increased the reserve power procurement cost.

4.3.2. Dynamic Programming (DP) and Rule-Based (RB) Techniques

The DP-based EMS approach was proposed [116] to determine the best operation for an isolated MG. This model incorporates the running cost of TGs and load-shedding penalty cost in the fitness function. The Pontryagin maximum principle was used to minimize the computation time of the DP model. The performance of the proposed method was validated by comparing its computation time and running cost with those of typical NLP and MILP models. This comparison proved that the recommended method is more efficient than conventional approaches. Similarly, in [117], a dynamic EMS approach was proposed to determine the optimal operating conditions for a grid-tied MG, aiming to reduce the energy exchange and battery aging cost. The proposed DP approach exhibited better performance than the RB approach. A deep-learning adaptive-DP-based EMS was presented in [118] in a real-time manner to maximize the RES utilization and minimize the emissions. The suggested approach also provides real-time control of the MG. The simulation results showed that the suggested approach could efficiently minimize both the running costs and environmental emissions.

A centralized RB EMS model for both standalone and grid-tied MGs was designed and simulated using the PSCAD/EMTDC software [119]. In the standalone approach, a fuel cell supplies power when the battery state of charge (SOC) is below 80%. The battery SOC should be above 60% for acceptable operation when connected to the UG. This RB method provides efficient switching between the two modes in terms of the frequency and voltage constant of the MG. An MG energy management approach involving prosumers using a system comprising PVs, an ultra-capacitor, and a battery was introduced in [120]. Two different EMS approaches were analyzed for the smooth operation of the MG. A central EMS was considered as an RB-optimization technique to regulate the MG operation, whereas a prosumer EMS controlled the fundamental frequency and balanced the power in the prosumer system. An improved real-time RB EMS was introduced in [121] to determine the best operating conditions for the MG by switching between the load-terminating mode and battery charging and discharging modes, based on the battery SOC and power generation discrepancy. A similar system was presented in [122] for developing a coordinated MG. To maintain the DC bus voltage in the steady-state, a PI-based controller is used to estimate the generation discrepancy, considering the PV power, battery SOC, bus voltage, and load demand as the input data. The BESS and UG adjust the power discrepancy.

The above studies mainly concentrated on managing various energy sources within MGs. An analysis of EMSs based on conventional techniques is presented in Table 10. Further study is required to assess the impacts of greenhouse gas (GHG) emissions from TGs on the environment, the effects of the depth of discharge (DOD) on the battery operation, consumer security and confidentiality problems, and the impacts of DR on the system reliability.

Table 10. Summary of conventional EMSs.

| Major Considerations | Research Objective | Suggested Technique | Limitations | Unpredictability-Handling Technique | Ref. |
|----------------------|---------------------|---------------------|-------------|-------------------------------------|------|
| Power trading; ESSs, fuel cell; energy consumption planning; minimize peak demand; | Optimal MG operation; ESS sizing; MG sizing | LP; MILP | Higher DOD, which leads to a quick degradation; No TG was incorporated to handle fluctuations of RES | Predicted; Predicted | [103] [104] |
Table 10. Cont.

| Major Considerations                              | Research Objective                                                                 | Suggested Technique       | Limitations                                                                 | Unpredictability-Handling Technique | Ref.   |
|---------------------------------------------------|------------------------------------------------------------------------------------|---------------------------|----------------------------------------------------------------------------|-------------------------------------|--------|
| energy trading                                    | Minimizing MG operating cost                                                     | MILP                      | Battery adoption was discouraged due to the higher investment cost          | Radial NN                           | [106]  |
| Includes energy trading, battery wear, and load-shedding penalty costs | Minimizing MG operating cost                                                     | MILP                      | Impacts of the EV plug-and-play feature were not considered in the MG performance | Predicted                           | [107]  |
| UG peak shaving; DR loads                        | Maximizing daily revenues                                                        | MILP; CPLEX software;     | ESSs were not considered; intermittency was not considered                  | Predicted                           | [108]  |
| Hybrid AC/DC MG                                   | Minimizing MG running cost; maximizing revenues                                  | MILP; CPLEX software;     | DR was not considered; the plug-and-play feature was ignored; computational complexity was ignored | Predicted                           | [109]  |
| Load-shedding cost; three-phase EMS power flow    | Minimizing MG running cost                                                        | MILP                      | DR and energy losses were ignored                                           | Predicted                           | [110]  |
| EMS for isolated MG; forfeit cost of reactive power | Minimizing fuel and operating cost of TGs                                        | MILP; NLP                 | DR was not considered                                                       | Predicted                           | [111]  |
| energy sharing; price bids for MG involvement in the electricity market | Minimizing MG operating cost; Maximizing revenues;                                | NLP                       | ESSs were ignored                                                           | Predicted                           | [113]  |
| voltage security; backward–forward sweep power flow | Minimizing MG operating cost                                                      | NLP                       | DER functional cost was overlooked                                           | Predicted                           | [114]  |
| resilient EMS; reserve power procurement approach | Minimizing generation and electricity exchange costs;                              | MILP                      | Uncertainty in generation was disregarded; DR was ignored                   | Predicted                           | [115]  |
| TG operating cost; load shedding cost             | Minimizing computation time                                                        | DP                        | DR was ignored; higher DOD caused rapid degradation                         | Predicted                           | [116]  |
| Dynamic energy prices                             | Minimizing energy exchange and battery aging cost                                 | DP                        | Computational complexity was ignored                                         | Predicted                           | [117]  |
| Deep-learning approach; real-time energy management | Maximizing the RES utilization; Minimizing emissions                              | DP                        | DR was ignored; RES uncertainty was ignored                                   | Predicted                           | [118]  |
| Fuel cell; PSCAD/EMTDC software                   | Optimal MG operation                                                              | RB                        | DR was overlooked; ESSs was disregarded                                      | Predicted                           | [119]  |
| Prosumer concept                                  | Optimal MG operation                                                              | RB                        | DR was not considered; emission cost was not considered                     | Predicted                           | [120]  |
| DC-bus voltage; battery SOC                       | Optimal MG operation                                                              | RB                        | DR and operating cost were not considered                                   | Predicted                           | [122]  |
4.4. EMS Considering Metaheuristic Approaches

4.4.1. Genetic Algorithm (GA)

A GA-based optimization technique was proposed in [123] to determine the optimal energy scheduling for a smart park based on an MG, using a price-dependent DR approach. The objectives of this system were to minimize the operating cost and maximize the utilization of RESs. The performance of the proposed approach was experimentally validated. GA- and RB-based multiobjective EMS models were developed in [124], considering battery deterioration and cost-effective load-dispatching from a remote MG. The models present real-time and day-ahead operations of the MG. The real-time approach incorporated a BESS, a diesel generator, and load termination choices to maintain generation balance. A modified GA was introduced in [125] to determine the best operation of a grid-tied MG by reducing the running cost of DERs. The efficiency of the suggested technique was better than that of a typical GA and other modified PSO algorithms. Furthermore, a GA-based EMS was proposed in [126] for reserve scheduling and optimal generation of a grid-tied MG. It employed a scenario-based probabilistic approach to defining the uncertain nature of wind speed and load demand. The fitness function considered various costs, such as the running cost, DR and load termination costs, active power reserve and reactive power support costs, as well as an automatically controlled switching cost. A matrix real-coded GA and ESS economical model-dependent smart EMS were introduced in [127] for a grid-tied MG. An NN approach was applied to predict solar power generation. This smart EMS managed the production, ESS bids, and energy-dealing revenue to reduce the MG’s running costs, while fulfilling the constraints of energy balance requirements and DERs.

4.4.2. Particle Swarm Optimization (PSO)

A PSO-based EMS for a coordinated MG was presented in [128]. This system used a point estimate method to determine the unpredictability of RESs, electricity prices, and load demand. The performance of PSO in obtaining an optimal outcome was better than those of GA and other modified PSOs. Similarly, the point estimate method was introduced in [129], using the Beta and Weibull probability density functions to represent the fluctuations in wind and solar power generation, and employing the robust optimization (RO) technique to model the variations in load demand. The proposed PSO-based EMS was employed to reduce the operating and maintenance and emission generation, as well as the reliability and security costs of an MG. A modified PSO was applied in [130] for optimal scheduling of RESs, to manage the unpredictability of load demand and power losses and reduce the electricity generation cost. The variations in load demand were managed using a scenario-based approach. The proposed approach showed promising outcomes of RES scheduling compared to other metaheuristic techniques. Another EMS was proposed in [131] to minimize the operating cost while satisfying system constraints in multi-energy carrier-based MGs. A Monte Carlo simulation was employed to predict the uncertainties in wind power generation, as well as electrical and thermal loads. A real-time DR approach was also utilized to dispatch controllable loads. The proposed model used PSO, showing better results than other traditional, centralized optimal scheduling models. Similarly, a new convergence-based PSO employing a Gaussian mutation method was introduced in [132] for an islanded MG. The fitness function comprised operating, maintenance, and capital costs of an MG. The suggested method was simulated on 69- and 94-bus islanded MG schemes. The modified GA outperformed the basic GA and other conventional PSO techniques.

An adaptive modified PSO-based multiobjective EMS was presented in [133]. This approach incorporated chaotic and fuzzy self-adaptive features to reduce the running and emission costs of a grid-tied MG. The proposed method showed better performance than that of chaotic and fuzzy self-adaptive-based PSO. A similar study was presented in [133]. The same authors aimed to reduce running and emission costs using a multiobjective-based PSO technique [134]. To achieve better operating conditions of MGs, an energy- and reserve-control approach was introduced in [135]. The targets were to reduce operating,
emission, voltage deviation, and energy-trading costs. The suggested method used affine arithmetic and a stochastic PSO-based optimal power flow technique.

4.4.3. Other Metaheuristic Techniques

A differential evolution method was proposed in [136] for an optimal EMS of a grid-tied MG. The study aimed to minimize operating and GHG emission costs by optimizing them independently. Moreover, the impacts of DR on reducing GHG emissions and peak-shaving demand were investigated. The performance of the suggested method in defining an optimal solution and convergence speed was better than that of PSO. An ant colony optimization-based EMS approach for a standalone MG was introduced in [137] to reduce the electricity production cost. The study fulfilled the requirements for typical operation, quick high load demand, and plug-and-play features, and reduced the MG’s functional cost by approximately 20% and 5% compared to typical EMS and PSO-based EMS, respectively. Similar to [126], a scenario-based EMS was proposed in [138] using a modified firefly technique to reduce the functional cost, taking into account the variations in the energy price, RESs, and load demand. A scenario-based approach employing a probability density function was used to predict system uncertainties. The efficiency of the suggested technique, regarding convergence speed and identifying the best outcomes, was better than those of the basic PSO, improved PSO, and GA. In [139], a novel probabilistic index, called an energy management success index, was introduced to minimize the total running costs of a multi-MG system, utilizing the tabu search algorithm. The proposed method incorporated a multi-state adjustable concept to define the unpredictability in EVs and RESs. Similar to the study in [114], this work used a backward–forward method, based on a stochastic power flow technique, to measure the power losses in the network. A multi-period artificial bee colony-based EMS was presented in [140] to achieve optimal dispatching, taking into account the generations, loads, and ESSs. An ANN method using a Markov chain was employed to predict the generation load demand fluctuations. The performance of an artificial bee colony-based EMS was compared to a traditional EMS and was then experimentally validated using an MG testbed. The results showed a 30% cost reduction and an increase in efficiency, even under intermittent conditions. An optimization approach to obtain the best configuration and EMS for an islanded MG was developed in [141] using the cuckoo search optimization technique. The study aimed to minimize the total cost, including operating, maintenance, investment, and capital costs. A new weighted-goal attainment function was utilized to limit emissions by implementing a tax on those emissions exceeding a certain value. This technique achieved an approximately 50% emission reduction. A cost-based model was proposed in [18] to optimize the BESS size in an RES-based MG. Since this system has various constraints, such as the power capacity of DGs and BESSs, the charge/discharge function of BESSs, and user satisfaction, this can increase the complexity of the problem. Thus, a modified bat algorithm was used to solve this problem and minimize the load dispatch costs. The outcomes show that the proposed technique decreased the charge/discharge frequency of BESSs and enhanced their durability.

The majority of these studies used a centralized supervision control for MG energy management, and only a few studies used effective unpredictability forecast techniques to consider the impacts of the MG output variations in obtaining continuous and reliable operation. Thus, additional research is required to construct a system that combines the following goals: reducing running costs, power system losses, battery degradation cost, and environmental pollution; adding a DR strategy; ensuring reliable MG operation; reducing the computational difficulty of the proposed optimization methods. Table 11 presents an analysis of EMSs, based on metaheuristic approaches.
Table 11. Summary of EMSs based on metaheuristic approaches.

| Major Considerations | Research Objective | Suggested Technique | Limitations | Unpredictability- Handling Technique | Ref. |
|-----------------------|--------------------|---------------------|-------------|-------------------------------------|------|
| DR approach; different tariff strategies for DR approach | Minimizing operating cost | GA | Unpredictability is ignored; power loss is ignored | Predicted | [123] |
| Battery deterioration cost; cost-effective load dispatch | Minimizing MG operating cost | GA | TG emission cost is ignored | Predicted | [124] |
| DER cost; optimal scheduling | Minimizing MG operating cost | Modified GA | ESS is not considered | Predicted | [125] |
| Active and reactive power reserve costs | Minimizing MG operating cost | GA | ESS is not considered; power losses are ignored | Scenario-based probabilistic approach | [126] |
| DER price bids | Minimizing MG running cost | Matrix real-coded GA | DR is ignored | NN approach | [127] |
| Fluctuations of generations, loads, electricity prices | Minimizing MG running cost | PSO | DR is ignored; TG emission cost is ignored | Point estimate method | [128] |
| Fluctuations of RESs | Optimal MG operation | PSO | Power losses are ignored; higher DOD, leading to quick degradation | Point estimate method | [129] |
| Load demand uncertainty; transmission power loss | Minimizing electricity generation cost | Modified PSO | DR is ignored; RES uncertainty is ignored; ESS is ignored | Scenario-based approach | [130] |
| Uncertainties of wind power generation; variations of electrical and thermal loads; DR approach | Minimizing operating cost | PSO | Energy losses are ignored; price variations are ignored | Monte Carlo simulation | [131] |
| MG operation, maintenance, and capital costs | Optimal MG operation | Convergence-based PSO | TG emission cost and power losses are ignored | Predicted | [132] |
| Day-ahead price forecasts | Reducing running and emission costs | Adaptive modified PSO | Sizing of the generators is ignored; DR is ignored | Predicted | [133] |
| Emission cost; energy trading cost | Optimal MG operation | Stochastic-PSO | DR is ignored; power losses are ignored | Affine arithmetic | [135] |
| DR approach; peak-shaving demand | Minimizing MG running and emission costs | Differential evolution | Battery DOD cost is ignored | Predicted | [136] |
| DR incentives; RES price bidding | Reducing electricity production cost | Ant colony optimization | TG emission cost is ignored | Predicted | [137] |
| Fluctuations of RESs; variable electricity prices | Minimizing MG running cost | Modified firefly | TG emission cost is ignored | Scenario-based probabilistic approach | [138] |
| Probabilistic index | Minimizing MG running cost; reducing power loss | Tabu search | Computational complexity is ignored | Scenario-generation approach | [139] |
| Fluctuations of RESs and load demand; DR approach | Minimizing MG running cost | Artificial bee colony | Battery DOD cost is ignored; power losses are ignored | NN with Markov chain method | [140] |
| Tax on emissions | Minimizing the total cost | Cuckoo search optimization | DR is ignored; computational complexity is ignored | Predicted | [141] |

4.5. EMS Based on Artificial Intelligence Methods

4.5.1. Fuzzy Logic (FL) and Neural Network (NN)

An FL-based EMS was proposed in [142] to obtain a stable power pattern from a grid-tied local MG. This approach reduced the power fluctuations around the peak demands by sharing energy with the UG. It also maintained the rated capacity of the battery SOC to increase its lifespan. Similarly, an FL-control-based EMS model was presented in [143] for a standalone DC MG. This model ensured the effective usage of RESs and improved
the lifespan of the Li-ion battery. In addition, the effectiveness and performance of this method were experimentally validated. In [144], a novel EMS was introduced to optimize the operation of a networked MG, which involves RESs and ESSs and coordinates with a minimal-capacity macro-grid. The FL approach was used to define the uncertainties in RESs, and a three-level optimization was conducted to determine the best MG scheduling. This approach was also employed in an actual case to evaluate its performance. A dynamic multiojective EMS was introduced in [145] to reduce the running and emission costs of MGs, wherein the battery discharging and charging rates were determined using the fuzzy expert method. The ANN technique predicts the fluctuations in the RES power generation and load demand. The efficiency of this method was better than that of the traditional approach, which does not employ a fuzzy expert method for battery scheduling.

A recurrent NN-based intelligent technique for EMSs was presented in [146]. The technique used an Ant–lion optimizer to reduce the electricity production cost and to maximize the utilization of RESs. The Ant–lion optimization technique was employed to define the economic dispatch problems in the system. The DR approach was used to define the optimal scheduling at a minimum electricity cost. The proposed model was implemented in a MATLAB/Simulink environment, and the results were compared with the results of other existing techniques for further validation. Similarly, a recurrent NN method was proposed in [147] to optimize the EMS of a grid-tied MG. This method aimed to maximize the use of power output obtained using RESs and reduce power trading (import) from the UG. A comprehensive Kalman-filter-based NN approach was employed to predict the RES power generation and load demands. A reinforcement-learning-based EMS was introduced in [148] to maximize the use of RES power and battery output, and to minimize the dependency on energy imported from the UG. The Markov chain method was used to forecast the uncertainties in wind speed. A deep NN load prediction technique was considered in [4] for short-term load forecasting, which resulted in an error reduction of approximately 30% compared to other existing techniques.

4.5.2. Multiagent Systems (MAS)

A MAS-based decentralized technique was proposed in [149] to optimize the operation of a grid-tied MG. All customers, ESSs, RESs, and UG were considered agents. The MAS-decentralized approach minimized the energy imbalance price while prioritizing the user energy consumption in the decision-making process. The results show that the proposed method achieved a more effective decision-making process than the centralized approach. Similarly, a MAS-based technique was proposed in [150] to model a smart EMS and construct a load-terminating strategy for a standalone MG. This technique can balance energy by coordinating among RESs, BESSs, and loads, in which BESSs and fuel cells were used as standby power sources. The uncertainties in RES generation, load demand, and atmospheric temperature were determined using the autoregressive-moving average technique. This technique significantly reduces the decision-making time. In addition, a static synchronous compensator (STATCOM) was used for voltage profile improvement and reactive power compensation, to minimize harmonics in the MG system. A MAS-based EMS was introduced in [151] for two interconnected MGs, to obtain optimal voltage regulation and improve the system stability under load variations and various weather conditions. The optimal MG activity was obtained using two-level optimization. The first and second levels involved optimizing the day-ahead energy and keeping the energy balance between generations and loads in real-time operation, respectively. Various strategies were presented to assess the performance of the proposed MAS. A harmony search algorithm was employed to reduce the running cost while supplying reliable high-quality power to the consumers. The outcomes indicated that an MAS could maintain system stability even if unexpected variations occurred in the generations and loads. A modified MAS-based EMS for the dynamic operation of a grid-tied home-based MG was investigated in [152]. The study aimed to decrease the running costs and fulfill customer requirements to maintain their comfort levels. A fuzzy cognitive maps-based
MAS technique was introduced in [153] to construct a dispersed EMS for a standalone MG. This approach reduced the MG running cost as well as the ESS and battery SOC forfeit costs. The proposed MAS-based method was designed and simulated using TRNSYS, MATLAB, GenOpt, and TRNOPT software packages.

4.5.3. Other Artificial Intelligence Techniques

A three-level Stackelberg game theoretical approach was proposed in [154] for developing an energy management model that coordinated among consumers, MG, as well as utility and energy storage companies. A big data-based generation-prediction technique was used to forecast short-term wind power. The optimization was conducted using a backward induction algorithm. The simulation results indicated that the proposed technique performed better than other traditional techniques. However, the study only considered a single MG and ignored the uncertainty in RES generation and energy consumption. Similarly, Stackelberg game theory was used in [155] to achieve the efficient EMS and energy-trading of a PV prosumers-based grid-tied MG. This method employed a leader–follower approach, in which MG works as a leader to maximize the profit and PV prosumers are followers, to maximize the usage of renewable generation. In this approach, a billing mechanism technique was used to control the variations in the PV power generation and load demand. A similar study proposed a leader-follower approach based on game-theoretic EMS with a DR program to achieve the same purpose [156]. An improved game theory-based multiobjective EMS was introduced in [157] to reduce the running and emission costs of a grid-tied MG. Furthermore, an improved intelligence approach was proposed to construct an EMS of a grid-tied MG using a hybrid ESS [158]. This approach aimed to optimize RES usage and reduce the load demand variations by taking into account the dispatch power errors. The load demand variations were controlled through the combined action of BESS and ultra-capacitors. The performance of the hybrid ESS in this technique was better than that in PSO.

Most of these studies focused on the reduction of the DER running cost, emissions, and energy exchange with the UG. Nonetheless, the computational difficulty of the proposed techniques, consumer privacy and security problems, and DR and MG system losses were not evaluated in detail. Other areas, such as a stable and reliable information exchange scheme for the dispersed operation of MG, the reduction of blackouts and interruptions, and the effects of DOD on the battery as well as on the MG performance, require further assessment. In addition, other topics, e.g., the inclusion of EVs in the DR program, as well as voltage and frequency profile adjustment to establish a sustainable and reliable operation of MG, should be investigated in future studies. Table 12 presents an analysis of artificial intelligence-based EMSs.

Table 12. Summary of EMSs based on artificial intelligence.

| Major Considerations | Research Objective | Suggested Technique | Limitations | Unpredictability-Handling Technique | Ref. |
|----------------------|--------------------|---------------------|-------------|-------------------------------------|------|
| Energy sharing; battery SOC | Minimizing power variations and peak demands | FL | Voltage and frequency controls are ignored | Predicted | [142] |
| Li-ion battery; usage of RESs | Optimal MG operation | FL | DR is ignored; battery SOC is limited | Predicted | [143] |
| Unpredictably of RESs and load demand; Energy trading; unpredictably of line capacity | Best scheduling of MG | Fuzzy MILP approach | DR is ignored; emission cost is not considered | FL | [144] |
| Unpredictably of RESs and load demand | Minimizing MG running cost Minimizing emission cost | FL | DR is ignored; computational complexity is ignored | ANN | [145] |
| Major Considerations                          | Research Objective                        | Suggested Technique | Limitations                                                                 | Unpredictability-Handling Technique | Ref.  |
|----------------------------------------------|-------------------------------------------|---------------------|------------------------------------------------------------------------------|-------------------------------------|-------|
| Battery SOC; DR approach                     | Reducing electricity production cost; maximizing RESs utilization | Ant–lion optimizer | Emission cost is ignored; no TG is incorporated to handle RES fluctuations; suboptimal solution | Predicted                           | [146] |
| Reducing power imports                       | Maximizing the use of RESs                | Recurrent NN        | DR is ignored; computational complexity is ignored                           | Kalman filter-based NN approach    | [147] |
| Hour-ahead RES forecasting                   | Maximizing the use of RESs and batteries  | Reinforcement learning-based NN | DR is ignored                                                                | Markov chain                        | [148] |
| Decentralized approach; energy consumption priority | Minimizing energy imbalance                | MAS                 | Charging/discharging effects are ignored                                      | Predicted                           | [149] |
| Using STATCOM to enhance PQ                  | Optimizing energy balance                 | MAS                 | Load shedding forfeit cost is ignored; RES and battery running costs are ignored | Autoregressive-moving average technique | [150] |
| Load variations; weather conditions           | Optimize voltage regulation and improve system stability | Harmony search algorithm | DR is ignored; emission cost is ignored                                       | Predicted                           | [151] |
| Battery SOC forfeit cost                     | Minimizing MG running cost                | MAS                 | DR is ignored                                                                | Predicted                           | [153] |
| Short-term forecast; coordination among agents | Maximizing profit                          | Backward induction algorithm | Uncertainty in RES generations is ignored                                    | Big data-generation prediction technique | [154] |
| Unpredictably of RESs and load demand;       | Optimal MG operation                      | Game theory         | ESS is not considered                                                        | Billing mechanism                   | [155] |
| Pareto optimal approach                      | Minimizing MG running and emission costs  | Improved game theory | DR is ignored; computational complexity is ignored                            | Predicted                           | [157] |
| Unpredictably of RESs and load demand        | Maximizing the use of RESs and minimizing the load variations | Improved intelligence approach | Charging/discharging effects are ignored; battery DOD cost is ignored         | Markov chain                        | [158] |

4.6. EMS Based on Stochastic and Robust Optimization (RO) Methods

A stochastic EMS for an islanded MG was introduced in [159] to reduce the application cost of ESSs and the forfeit cost on load termination and dumped power. A scenario tree-based technique was introduced to account for the unpredictability of RESs and load demand. This method aimed to achieve higher reductions in the MG running costs than those achieved by the forecast- and SOC-based EMSs. A two-level stochastic EMS was proposed in [160] for the active energy management of a grid-tied MG. This approach determined the optimal day-ahead MG operation at the former level and implemented AC-load flow in real-time operation to determine the power network losses at a later level. The performance of the suggested approach was verified in an IEEE 37-node system. Similarly, a two-level stochastic EMS approach was proposed in [161,162] to enhance the performance...
of a grid-tied MG, taking into consideration the fluctuations in RESs and load demand. The first level focused on minimizing the MG implementation costs, and the second level used an EMS to determine the best operation of MG. The impacts of battery SOC and BESSs on the buying and selling power were also investigated under various scenarios.

An RO technique with a dispersed EMS, which used an agent-based model for a grid-tied MG, was introduced in [162] to enhance system reliability. The performance of this approach was evaluated based on the imbalance cost caused by fluctuations in energy prices, RESs, and load demand. The variations in RES power generation, load demand, and electricity prices were predicted using a nondominated sorting GA-trained NN. A scenario-based RO technique was introduced in [163] to improve the worst-case scenario in energy planning for a grid-tied MG. The unpredictabilities of generations and demands were introduced using the interval prediction theory. An enhanced EMS method was utilized to reduce the social benefit/cost of an MG, which consists of the running costs of TG and BESS along with the worst cost of energy trade-off. Similarly, the social benefit/cost was minimized for a grid-tied MG in [164] using a robust decentralized EMS approach. A two-level RO-based grid-tied MG EMS model was proposed in [165,166]. It introduced the day-ahead optimal operation in the first level and the energy trading, as well as real-time cost-effective dispatch operation, in the second level. The complexity of this approach was simplified using the Lyapunov optimization technique. The performance of the suggested method was better than that of the greedy method. The two-level model introduced in [165] was converted into a MILP problem, which was resolved by a column-and-constraint generation technique.

The main shortcomings of the above methods include the difficulty in the formulation of optimization problems, computation speed, the high range of battery DOD, and consumer privacy and security problems. Table 13 presents an analysis of stochastic- and RO-based EMSs.

Table 13. Summary of EMSs based on stochastic and RO methods.

| Major Considerations | Research Objective | Suggested Technique | Limitations | Unpredictability-Handling Technique |
|----------------------|--------------------|---------------------|-------------|-------------------------------------|
| Unpredictability of RESs and load demand; forfeiting cost on load termination | MG running costs | Stochastic optimization | DR is ignored; more complex problem | Scenario-based approach [159] |
| TG operating cost; energy trading cost | Minimizing MG running cost | Stochastic optimization | Computational time is neglected; higher DOD, leading to quick degradation | Monte Carlo approach [160] |
| Fluctuations in RESs and load demand; battery SOC | Minimizing investment cost; minimizing MG running cost | Stochastic optimization | Emission and battery degradation are ignored | Scenario-based approach [161] |
| Power imbalance cost; fluctuations in RESs and load demand | Optimal MG operation | RO | DR is ignored; more complex problem | Nondominated sorting GA-trained NN [162] |
| Worst-case scenario in energy planning; unpredictability of generations and demands | Minimizing TG running cost; minimizing energy trading cost | RO | DR is ignored; emission cost is ignored | Interval prediction theory [163] |
| Day-ahead unit commitment | Optimal MG operation | RO | Computational time is ignored; higher DOD, leading to quick degradation | Predicted [165,166] |
The comparison between various EMS techniques is shown in Table 14. It can be interpreted that none of the techniques is accurate, as each technique has its own advantages and disadvantages.

Table 14. Comparison of various EMS techniques.

| EMS Technique                        | Advantages                                                                 | Disadvantages                                                                 | Improvement                                      |
|--------------------------------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------------|-------------------------------------------------|
| Conventional technique               | High precision factor; requires less computational time                      | Hard to implement for the large system; limited space optimization             | Apply advanced mathematical techniques           |
| Metaheuristic technique              | Easy to implement; Capable of handling complex problems; deals with numerous variables | Relatively lower performance for determining global optimal solution; premature convergence; requires a long computational time | Requires advanced heuristic strategies           |
| Artificial intelligence technique    | Efficient performance for determining global optimal solution; capable of handling complex problems | Relatively hard to code                                                        | New deep-learning methods could improve the EMS |
| Stochastic and robust optimization technique | Capable of handling complex problems                                          | Computational time complexity is higher; complex formulation                  | -                                               |

5. Challenges and Recommendations

MGs are a potential technology that can enhance the reliability and energy supply, to maintain consumer satisfaction. This research discusses various IDTs, EMSs and operations of MGs to present useful suggestions for providing reliable and viable energy to consumers. However, some challenges require the attention of future researchers.

5.1. Islanding of MGs

Islanding is an unwanted situation because it contributes to PQ problems and may lead to human injuries. Furthermore, islanding may damage the generation and supply facilities because of voltage, frequency, impedance, and power mismatches. Thus, monitoring MG operating conditions is an important factor for optimizing MG operations. Effective IDTs are essential for identifying the correct operation state. Several studies have used different IDTs to identify islanding [36], but most of them have large NDRs, resulting in false detection. Therefore, a proper IDT with a minimal NDR is required to identify MG islanding. More studies also require developing new IDTs for integrated power networks. This development can not only provide ID options but can also be useful for academic research and industrial applications.

5.2. Cost Minimization

Operating cost minimization is one of the most important aspects of MG EMS. The inclusion of DERs, RESs and BESSs can significantly reduce the MG operation and emission costs. However, the uncertain nature of MG components and the high dimensionality of their variables must be considered because the power production by RESs and intermittency, owing to their stochastic behavior, is challenging to forecast. A slight enhancement in forecast models can contribute to considerable financial savings [167]. Thus, an accurate forecasting approach is imperative, not only for the short term but also for the long term. Numerous studies have investigated this problem to resolve the uncertainties for MG, but an extensive approach should be conducted if various uncertain variables are present at the same time.

BESSs are important for MGs to ensure uninterrupted facilities. They strengthen MGs through backup power and other energy management services. However, BESSs are
not easy to integrate, and they have their own limitations. Studies on BESSs should be performed with the incorporation of industry compliance, cost-competitive systems, safety and security [168].

5.3. EMS of MG

An EMS is imperative to obtain the optimal operation of MG while satisfying all the constraints. The outcome of an EMS is dynamic in nature and is challenging to anticipate because of the dynamic behavior of users and energy sources. Designing an EMS that can accommodate dynamic behavior in real time, depending on current status, is still a complicated challenge. In the literature, different techniques and approaches have been investigated to establish robust EMSs [169]. Nonetheless, this does not always work when highly unpredictable behaviors of the sources are present. Therefore, smart EMSs with advanced optimization techniques are required to optimize MG energy management in real-time and day-ahead schemes.

5.4. Protection

In MGs, current flows in both directions and its magnitude may vary because of their dynamic structure (DGs and loads can frequently change). Thus, MG protection is crucial because the fault current magnitude in an MG relies on its operating modes. The fault current, such as the short-circuit current, may damage system components and user equipment. Therefore, protective relays and energy circuit breakers are required to detect abnormal situations and prevent faults, respectively [170]. A few studies have proposed different protection strategies for MGs [171,172]. However, a new protection solution strategy that integrates protective devices is required to prevent tripping problems.

5.5. Reliability

MGs can be considered as micro-power systems that involve numerous DGs, RESs and ESSs to maintain PQ and system reliability. With the increasing integration of RESs, the power network becomes complex and difficult to manage and control, owing to their uncertainties. The RESs uncertainties, switching operations, and variable loads affect the reliability of the system. Thus, a reliable, advanced control system is required to minimize the components causing uncertainties. Moreover, MGs may even operate under unbalanced conditions (voltage and frequency mismatches with the UG) that reduce PQ and reliability. Therefore, a hybrid micro inverter is required to reduce the voltage imbalance and THD to improve PQ and power-sharing between MGs [173]. Furthermore, MGs reliability analysis is not investigated in detail regarding islanding and remote operations. These potential sectors require studying in detail to obtain an optimal energy operation of MGs.

5.6. Efficiency

The concept of MGs and their efficiency concerns managing multiple loads and matching them to DG sources. MGs can run on a diversity of power sources, such as RESs, natural gas-based turbines or fuel cells. MGs can limit enormous energy losses by taking power directly from the cheapest sources. However, integrating and controlling different sources during MG operation remain challenging issues. Therefore, a proper control method is required to enhance the efficiency of MG systems. The control of the smart grid, hybrid controller and fast transfer switching can be applied in an MG to enhance the overall efficiency. The smart inverter can be employed for compensating both the active and reactive power to enhance system efficiency.

These recommendations aim to improve existing MG technologies and help future research to reduce the limitations of typical MG technologies, to increase their share in the electricity market.
6. Conclusion and Future Prospects

MGs usually comprise DERs, DR, EVs, local and central controllers, EMSs, and communication devices. This review presents an extensive and critical analysis of the approaches and solution techniques in the case of IDTs and MG EMSs. Effective IDTs are essential for determining the best operation of MGs. This paper intends to present the development of performance indices (the non-detection region, error detection ratio, detection time, PQ, the effect on the MG, and implementation costs) to assess various IDTs. The applicability of each IDT is discussed, which should help researchers select the proper IDTs. EMSs are used to determine the optimal operation, reliability, and energy scheduling in both MG operating modes for sustainable improvement. An MG EMS is a multiobjective approach that considers different aspects of the system, including the technical, economic, and natural aspects.

This comprehensive review focuses on opportunities, solutions, and future aspects to determine islanding and achieve the EMS objectives using different techniques. The approaches discussed herein focus on several aspects of the system, including the operation schemes, MG operation (integrated or dispersed), the intermittency of RESs, the DR program, battery status, economic aspects, the emission problems of traditional generators, consumer security and privacy, power network losses, and reliability. Several studies have considered some of these features. Nonetheless, more research is required to obtain optimal, cost-effective, and energy-efficient operation of MGs. Many studies can be conducted in the future, based on the following directions:

- An intelligent technique, along with an advanced signal processing unit, can be an effective tool for ID. Various devices like smart meters, phasor measurement units, and so on, can be applied for ID. This can significantly reduce the implementation time and cost, making it practical and economically viable.
- Advanced research is needed to enhance a next-generation BESS in MG applications. Some issues of BESSs, such as materials, cost, size, control interface, and safety can be considered to achieve correct functionality and market recognition.
- A better forecasting model can reduce daily expenses. Intelligent and robust forecasting models can be employed that can benefit both consumers and operators, as well as minimizing daily expenses.
- In the MG EMS, more functions can be studied as objectives, such as the PQ index, equipment lifetime and consumer security. In the control aspect, the load control approaches should be studied more than in the past.
- An optimal EMS with an advanced BESS approach can be a great choice for prospective development, to enhance the overall system efficiency and minimize the cost.
- Enhanced meta-heuristic techniques have been applied for MG EMS; new solvers can be employed for simplification and to hasten the solving process.

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### Acronyms

| Acronym | Description                        |
|---------|------------------------------------|
| AC      | Alternating current                |
| AFD     | Active frequency drift             |
| AFDPF   | AFD with positive feedback         |
| ANN     | Artificial neural network          |
| BESS    | Battery energy storage system      |
| DC      | Direct current                     |
| DER     | Distributed energy resource        |
| DG      | Distributed generation             |
| DOD     | Depth of discharge                 |
| DP      | Dynamic programming                |
| DR      | Demand response                    |
| DT      | Decision tree                      |
| DWT     | Discrete wavelet transform         |
| ED      | Error detection                    |
| EMS     | Energy management system           |
| ESS     | Energy storage system              |
| EV      | Electric vehicle                   |
| FJ      | Frequency jump                     |
| FL      | Fuzzy logic                        |
| GA      | Genetic algorithm                  |
| GHG     | Greenhouse gas                     |
| ID      | Islanding detection               |
| IDT     | Islanding detection technique      |
| IM      | Impedance measurement              |
| LP      | Linear programming                 |
| MAS     | Multi-agent system                 |
| MILP    | Mixed-integer linear programming   |
| MINLP   | Mixed-integer nonlinear programming|
| MG      | Microgrid                          |
| NDR     | Non-detection region               |
| NLP     | Nonlinear programming              |
| NN      | Neural network                     |
| NP      | Linear programming                 |
| NSC     | Negative-sequence current          |
| PCC     | Point of common coupling           |
| PF      | Power factor                       |
| PLL     | Phase-locked loop                  |
| PLCC    | Power line carrier communication   |
| PNN     | Probabilistic neural network       |
| PQ      | Power quality                      |
| PSO     | Particle swarm optimization        |
| RCF     | Rate of change of frequency        |
| RCP     | Rate of change of power            |
| RCV     | Rate of change of voltage          |
| RES     | Renewable energy resource          |
| RO      | Robust optimization                |
| SCADA   | Supervisory control and data acquisition |
| SFS     | Sandia frequency shift             |
| SGD     | Signal generated by disconnection  |
| SMFS    | Sliding mode frequency shift       |
| SOC     | State of charge                    |
| STATCOM | Static synchronous compensator     |
| SVM     | Support vector machine             |
| SVS     | Sandia voltage shift               |
| TG      | Traditional generation             |
| THD     | Total harmonic distortion          |
| UGF     | Utility grid                       |
| UOF     | Under/over frequency               |
| UOV     | Under/over voltage                 |
| VU      | Voltage unbalance                  |
| WPT     | Wavelet packet transform           |
| DWT     | Discrete wavelet transform         |

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