Energy and AI 8 (2022) 100147

Contents lists available at ScienceDirect

Energy and AI

journal homepage: www.sciencedirect.com/journal/energy-and-ai

Review

Implementation of artificial intelligence techniques in microgrid control environment: Current progress and future scopes

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ARTICLE INFO

Keywords:
Artificial intelligence
Microgrid control architectures
Hierarchical control
Networked microgrids
Machine learning
Distributed energy resources

ABSTRACT

Microgrids are gaining popularity by facilitating distributed energy resources (DERs) and forming essential consumer/prosumer centric integrated energy systems. Integration, coordination and control of multiple DERs and managing the energy transition in this environment is a strenuous task. Classical control techniques are not enough to support dynamic microgrid environments. Implementation of Artificial Intelligence (AI) techniques seems to be a promising solution to enhance the control and operation of microgrids in future smart grid networks. Therefore, this paper briefly reviews the control architectures, existing conventional controlling techniques, their drawbacks, the need for intelligent controllers and then extensively reviews the possibility of AI implementation in different control structures with a special focus on the hierarchical control layers. This paper also investigates the AI-based control strategies in networked/interconnected/multi-microgrids environments. It concludes with the summary and future scopes of AI implementation in hierarchical control layers and structures including single and networked microgrids environments.

1. Introduction

Microgrids can be distinguished from any distribution network containing DERs by two distinct features. First, their capabilities to operate in an islanded mode confirms the resiliency and reliability of the network. Second, to appear as controlled and coordinated units viewing from the upstream network [1]. Microgrids provide noteworthy benefits to consumers as well as utilities, the majority of which include; higher reliability by incorporating flexibility at the community layer distribution network, improved power quality by managing flexible loads, reduced carbon emission by the diverse DERs, lowering transmission & distribution losses, cheap energy supply utilising more renewable resources, and the possibility of active participation in the energy markets [2], and must fully satisfy the network and load requirements at islanded mode [3].

Taking into consideration the large share of stochastic natured DERs comes with lots of uncertainty and a range of instances where effective controlling of the microgrid network becomes very critical. Interconnecting multiple microgrids as a network of microgrids can be an effective solution to accommodate and improve the operation quality of the large number of DERs. It has also been recognised that when multiple microgrids, geographically close to each other, are tied together through the distribution line to form a networked microgrid, the reliability and resilience of the interconnected microgrid can be significantly increased [4, 5].

Artificial Intelligence (AI) is a branch of computer science that has become popular in recent years. In the context of microgrids, AI has significant applications that can make efficient use of available data and helps in making decisions in complex practical circumstances for a safer and more reliable control and operation of the microgrids. The advancements in AI-based algorithms and computational capacity with a large amount of data processing abilities are well enough to exploit the single to multi-microgrid network controlling environment. Machine learning (ML) and deep learning (DL) are important subsets of AI. In general, ML and DL models can be supervised or unsupervised depending upon the input training data. In the context of microgrids, the system control and analysis need an advanced approach that not only depends on the physical model but also integrates the data-driven modelling to better address the observability and controllability issues [6]. Considering the level of control, communication requirements and energy resources, the microgrid hierarchical control scheme have multiple control layers depending upon the functionality to be addressed [7]. Adjoining AI techniques with these existing schemes can bring higher accuracy, speed and better effectiveness for control and operation in a microgrid environment [8]. Conventional control methods are

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https://doi.org/10.1016/j.egyai.2022.100147

Available online 2 March 2022

Abbreviations

Controller type
Proportional integral controller PI
Model predictive control MPC

AI Technique
Neural network NN
Support Vector Machine SVM
Artificial neural network ANN
Deep reinforcement learning DRL
Multi-layer perceptron MLP
Back propagation neural network BPNN
Long short-term memory LSTM
Feed forward Neural network FFNN
Adaptive neuro-fuzzy inference system ANFIS
Single hidden layer feedforward neural network SLFN
Fully connected network FCN
Recurrent neural network RNN
Support vector regression SVR
Elman neural network ELN
Deep neural network DNN

also model-based which require sufficient information and understanding of system dynamics. ML algorithms particularly Deep Reinforcement Learning (DRL) is considered a promising means to develop a model-free design where DRL focuses on the physical model learning from the environment and maps inputs to the actions [9].

Rapid advancement in microgrids research, demonstration, and deployment (RDD) in the past and recent years reflect the value of microgrids in the future development of decarbonised smart grid networks. Over the last decade, plenty of literature reviews has been done on different areas of microgrids to find out the RDD status, challenges, progress and future scopes. A summary of some of the most important review papers that have been published in high-impact factor peer-reviewed journals and transactions is presented in Table 1. It shows that microgrid controls have been reviewed most which are followed by the protections, architecture and topology, energy management and integration of energy storage (ES). Implementation of AI techniques in microgrid controls is also gaining importance these days. A review on the progress of AI implementation appears in [89] which focuses more on the microgrid stability issues. Authors in [30] also have reviewed the progress on ANN implementation but were limited to a single microgrid only. By this time, a large number of researches have been conducted on different AI techniques to demonstrate their applicability in power systems, microgrids control, operation and management areas. This includes single to networked microgrids environment. Hence, we have reviewed the current progress on the implementation of AI techniques with a special focus on the control and functionality at different hierarchical control layers. The review has also been extended to networked microgrids environments.

The highlights of this paper are:

- The conventional microgrid control architecture is not suitable for a dynamic microgrid environment
- Implementation of AI techniques can adapt and enhance the smooth control and operation of microgrids in various control environments.
- AI techniques empower the hierarchical control layers. Key features where specific AI techniques can further be implemented are outlined.
- Multi/Networked/Interconnected microgrids structure have a wide range of controlling objectives where AI can efficiently facilitate the complex control objectives.

Table 1
Existing review papers on different areas of microgrids

Ref	Review area	Published year
[10, 2]	Challenges, and research needs	2010, 2015
[11, 12]	AC versus DC: Resources and technology	2013, 2014
[22, 6, 13-40],	AC: Control strategies	2014 - 2018, 2021
[16–17]	Architecture and topology	2013, 2015, 2017
[23-28, 17, 18],	AC, DC, Hybrid: Control techniques	2011, 2013 - 2015, 2017
[19, 20]	DC: Hierarchical control	2015, 2020
[21]	Building microgrids: Hierarchical control	2019
[45,24]	Protection schemes	2014 - 2016, 2018, 2020
[25]	Adaptive protection based on communication	2021
[26, 27]	DC: Protection	2018, 2019
[28]	Modeling uncertainties	2017
[29–30]	EMS	2015, 2018 - 2020
[31]	DC: Architectures, Applications, and Standardization	2016
[32, 33]	Power sharing	2016, 2017
[34]	Islanded: EMS and planning	2019
[35]	Operation, applications, modeling, and control	2021
[36]	Generation, demand forecasting	2018
[37, 38]	Experimental microgrids and example cases	2010, 2011
[39]	DC: Planning, operation and control	2021
[40, 41]	DC: Control, power sharing and stabilization techniques	2016, 2019
[42]	Stability improvement	2017
[43]	Reactive power compensation	2018
[44]	Value streams	2016
[89, 6]	Implementation of AI and ANN in control	2017, 2020
[45–47]	Hybrid/Energy storage/Flywheel application	2017, 2019
[48]	Technologies, key drivers, and outstanding issues	2018
[49]	Transactive Energy Market	2020
[50]	Guidelines for practical implementations and operation	2020
This paper	Implementation of AI techniques in control (single and networked microgrids)	2021

The rest of the paper is organised as follow: Section 2 summarises the review study on control architectures along with their control and operational features. In section 3, an overview of AI techniques has been presented, followed by the implementation of AI in hierarchical control in section 4 with detailed reviews and possible improvements. Section 5 comprises networked microgrids architecture and section 6 reviews the implementation of AI in that environments. Section 7 discusses the findings and future scopes on AI-based microgrids control followed by the conclusion in section 8.

2. Microgrid Control

2.1. Conventional control

The key control and operational features of the conventional control architecture are recapped in Table 2. It can be summarised from the comparisons that with the increasing penetration of DERs in the distribution network, distributed control approach will play an important role in decarbonising the future distribution or island grid. From the control features point of view, it is highly effective but the complexity to achieve is also high.

2.2. Hierarchical control

The primary layer is generally responsible for droop control to make the system stable and damped by emulating the physical behaviour of the system which can be realised by adding a virtual impedance control loop. The complex controlling is achieved by local controllers and hence this layer has a very fast or real-time response. A master-slave control is also proposed in [51] where one of the converters acts as master and

Table 2
Comparison of conventional control methods concerning control & operational features

Control Features	Centralised	Decentralised	Distributed
Voltage stability	Less effective in multiple DER units	Effective and realisable	Highly effective but complex to achieve
Frequency regulation	Less effective in multiple DER units	Effective and realisable	Highly effective but complex to achieve
Load-frequency control and error minimisation	Effective and realisable	Less effective, no global controllability is possible	Highly effective but complex to achieve
Power-sharing	Less effective in multiple DER units	Effective and realisable	Highly effective but complex to achieve
Optimal power flow	Effective but complex to achieve	Less effective, no global controllability is possible	Highly effective but complex to achieve
Energy management	Effective but complex to achieve	Less effective, no global controllability is possible	Highly effective but complex to achieve
Other Operational Features			
Control layer	Single control	Multiple	multiple
Implementation	Easy	Moderate	Complex
Goals	An explicit single task	Multiple tasks	Variable and uncertain
Flexibility	Low	Moderate	High
Communication	High	Low	Medium
Reliability	Single point failure	Multiple points	Multiple points
Scalability	Low	moderate	high
Plug-and-play	Hard to achieve	Achievable	Achievable

others as slaves. There must be a communication channel established for coordinated control of master and slave controllers itself which could be a possible hurdle for local controllers. Hence, a secondary control layer is mainly responsible for managing and compensating the voltage and frequency deviations caused at the primary layer. In addition, it also facilitates the synchronised control loop for efficient and flawless connection and disconnection from the main grid. Tertiary control is the highest layer of control in a hierarchical scheme. It ensures the optimal power flow and energy management between the microgrid and the main grid.

Extensive reviews have already been done on the hierarchical controls. Authors of this paper have drawn, as shown in Fig. 1, a summary of the functionalities and the control methods in the hierarchical structure that have been well researched and reviewed by the researchers in references as shown in Tables 1 and 3. Review contributions from the authors of this paper are also outlined in Table 3. When it comes to AI implementation, authors in [52] reviewed mainly NN-based controlling in microgrids which appears as shallow research. Researchers in [6] have considered only MPPT as the major primary control objective whereas our work considers real-time power-sharing and inertia estimation as crucial primary control objectives that are missing in most of the research work. Moreover, the networked microgrid is not thoroughly explored in any of the previous review papers. We have considered nearly all the missing gaps in existing research work and future directions required for efficient control in networked microgrids. Thus, this paper presents a whole extensive review of AI techniques implemented in hierarchical and networked microgrid control.

3. Overview of AI framework for microgrid control

Machine learning is one of the subsets of AI, has the potential to improve the operation and control of microgrids. ML can be broadly categorized into four types according to the method of learning namely: supervised, unsupervised, semi-supervised and reinforcement learning. An overview of these categories including some examples of research work on their implementation in the smart grid areas are briefly summarised below. The authors also reviewed that these could easily be incorporated in microgrid control research which has been reviewed and explained in detail in the following sections.

3.1. Supervised learning (SL)

Supervised learning is defined as a process where the labelled datasets are used to train the algorithms to either classify or predict the continuous value target feature(s) [60] [61]. Classification and regression are two major categories in this learning. For control in microgrids, the classification problem can be applied to detect the disturbances due to load change [62], transient conditions [63] and can further be

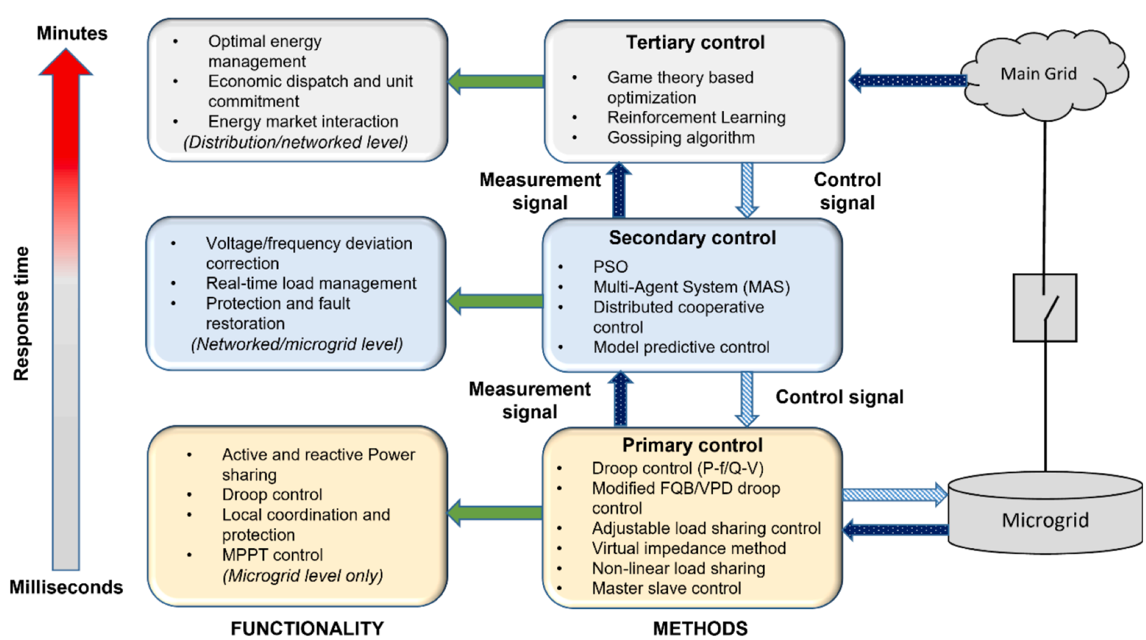

Fig. 1. Hierarchical control functionality and control methods

Table 3
Comparison of proposed work with existing methods

Ref	Conventional control	Hierarchical control	AI-based Hierarchical control Primary	Secondary	Tertiary	AI-based networked -microgrids control
[35]	✓	✓	×	×	×	×
[53]	✓	✓	×	×	×	×
[54]	✓	✓	×	×	×	×
[55]	✓	✓	×	×	×	×
[56]	✓	✓	×	×	×	×
[57]	✓	✓	×	×	×	×
[58]	×	×	×	×	✓	×
[21]*, [59]*	✓	✓	×	×	✓	×
[6]*, [52]*	×	×	✓	✓	✓	×
This paper	✓	✓	✓	✓	✓	✓

* Not comprehensively reviewed

extended to power quality [64], voltage stability assessment [65] and fault detection and classification [66]. Forecasting problems can include prediction of PV generation [67], electricity demand [68], electricity market pricing [69] etc.

3.2. Unsupervised learning (UL)

This type of algorithm works well for analysing and clustering unlabelled datasets. It is defined as the algorithm that can learn the patterns and trends available in the untagged dataset without the need for human supervision and predict for all unseen values [60]. It makes learning faster and easier. Clustering is a class where the entity segmentation and various patterns in the data are discovered automatically. From the microgrid point of view, load profile clustering [70, 71], consumer/prosumer segmentation [72], network topology identification [73] fall under unsupervised learning.

3.3. Semi-supervised learning (SSL)

In recent years, both labelled and unlabelled data has been used to train machine learning models. The technique of making the model to learn from labelled and unlabeled datasets and predicting for all future points is defined as semisupervised learning[60]. One of the most popular algorithms for this method is called Generative adversarial networks (GAN) [74, 75]. In the microgrid context, SSL such as GAN architecture has the potential to generate the trained data from noise and minimise the gaps between trained and real data to generate time-series power generation profiles of DERs [76], schedule the energy storage for solar PV microgrid [77]. GAN can also be integrated with RL and DNN to provide real-time control in microgrids [78].

3.4. Reinforcement learning (RL)

Reinforcement learning (RL) is a unique algorithm that consists of environment, agent, reward and action. RL is defined as the learning process in which, the agent actively interact within the environment to gather the information and sometimes affect the environment as well, and receives a reward for each action[60]. Collectively, it aims to maximise the total reward after following through a continuous process of obtaining rewards and punishments on different actions. RL has the potential to enhance the decision-driven control and operation of the microgrid. Optimal energy management [79], autonomous electricity market participation [80], multi-microgrid interaction and management [81] are the key areas where RL has been exploited. The schematic representation of AI techniques that can be implemented in microgrid control is shown in Fig. 2.

The overview of AI-based techniques for various parts of the microgrid research is shown in Fig. 3. From the core element and control point of view, the five categories have been defined namely, DERs, load, weather forecast, energy market and main grid with each category having a specific set of objectives and the AI techniques associated with each objective are shown there. It comprises classical control infused with hierarchical control functionalities. Primary and secondary control mainly include MPPT control, voltage and frequency control, power-sharing, protection, fault restoration and high-speed communication. Tertiary control at the high level includes energy management, power flow management within microgrid and with the external grid, prosumer autonomous market participation, customer segmentation and forecasting (load, generation and market prices). NN-based algorithms have been implemented mostly in all three hierarchical control layers. Apart from it, for classification and clustering purposes, CNN and K-NN techniques also have been studied in some of the works. The use of RL has emerged as a potential technique in power-sharing and the energy market in microgrid control applications. Some review progresses have already been made on forecasting of load demand [82–83], energy generation [84–85], and market prices [86–87] and hence considered the out of scope of this paper.

4. AI in Hierarchical control – review and possible improvement

This section is significantly reviewed the research work where the AI techniques have been implemented in the hierarchical control layers.

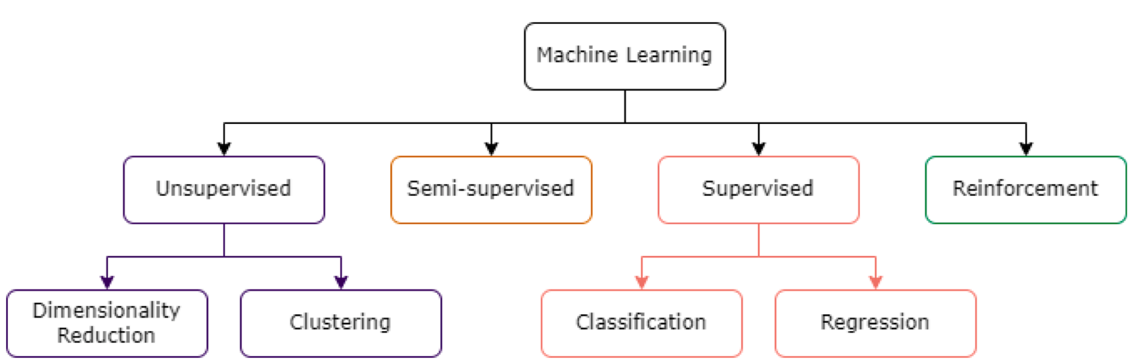

Fig. 2. AI techniques that can be implemented in microgrid control

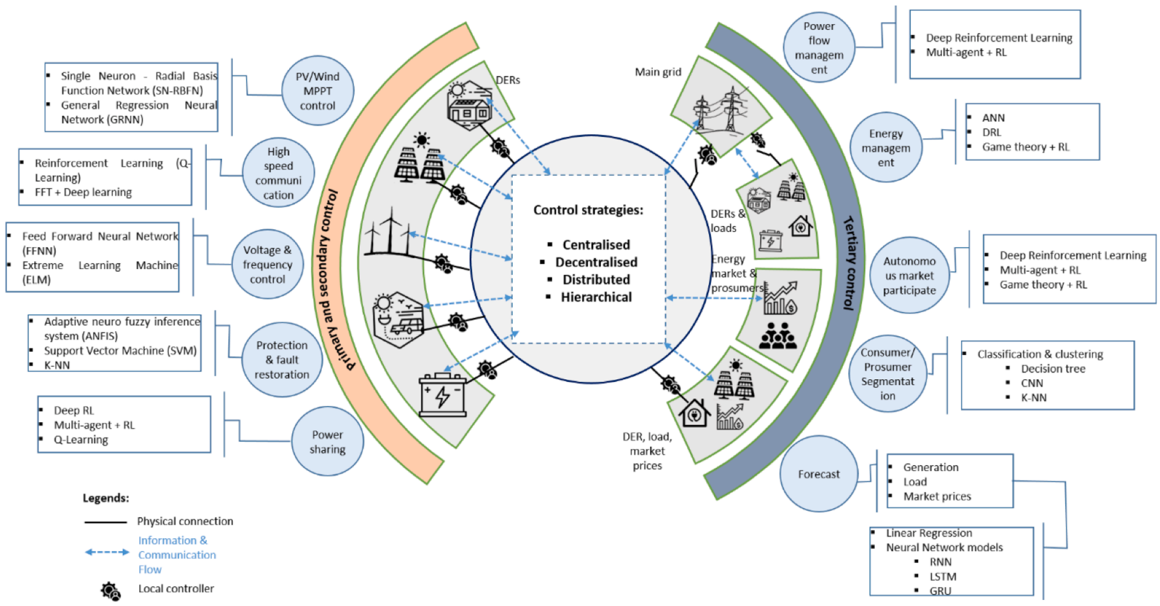

Fig. 3. Overview of AI techniques in various microgrid control and functionalities

Authors also have taken the opportunities to recommend the possible improvements that can be considered as future scopes. The findings are also summarised in section 7.

4.1. Primary Control

Conventional droop control methods lack accuracy, speed and robustness [88]. Embedding AI to the existing control techniques can enhance the control functionality in the microgrid environment [7]. Under the hierarchical control structure, the primary control layer mostly focuses on (i) real-time power-sharing, (ii) MPPT control and (iii) inertia control. Energy storage (ES) brings the benefit of dealing with uncertainties associated with the stochastic natured DERs but the power-sharing mechanism can be a complex task. The droop control with power-sharing should deal with this issue and AI has again, plenty of opportunities to enhance the controlling in microgrids which have been discussed in this paper. Research findings show that the MPPT systems with conventional control methods suffer from slow tracking speed and complex system-based design [89]. The NN-based AI technique can track the MPP more accurately with an error of less than 0.1% [89]. AI in primary control is improving the inertia level in rotation-less DERs in microgrids. Existing control methods in this area are based on complex model-based design and can not provide optimal control and hence affect the primary control operation. Bringing AI techniques to estimate and forecast the inertia in real-time can be an interesting area of future research and has been discussed in respective sections.

4.1.1. Real-time power-sharing and ES: coordination and control

It is already identified that NN-based solutions have widely been implemented in all control layers. ANN-based droop control is proposed in [90] to improve the accuracy of active/reactive power-sharing and simultaneously control the voltage and frequency in the microgrid. The proposed ANN technique follows the feed-forward NN (FFNN) which is trained by a Levenberg-Marquardt (LM) algorithm. The solution shows that the current sharing error can be reduced to 0.3A, compare to 1.5A in the case of a conventional controller. The ANN-based framework with droop control to control the parallel-connected units in a standalone DC microgrid [91]. This strategy works very well to maintain the voltage and coordinated power-sharing in sudden load disturbance events. However, it doesn't consider the SoC balance of multiple storage units. Authors in [92] have presented a virtual energy-based droop control mechanism considering SoC and power-sharing powered by an intelligent adaptive control strategy wherein the virtual resistance and reference voltage are generated by time-dependent parameters of the storage system itself. A coordinated control is provided in [93] for Grid-PV-ESS integrated system through a Bus-Signalling primary control in which control modes of the individual units are designed according to the virtual reference parameters of the ESS. It promises significant advantages over traditional droop control like maximising the PV utilisation, effective power-sharing and voltage stability. In multiple case scenarios that include control actions for transient due to loads switching, DC fault performance of a system is analysed in which it is shown that the control system is capable enough to maintain the bus voltage within the range 0.975 pu to 1.025 pu in all cases. Another ANN-based dynamic power management strategy is proposed in [94] where the NN algorithm considers the reference current and the SoC value to control the voltage at DC bus in case of load and generation fluctuations. An adaptive control scheme integrating fuzzy logic and the neural network has been presented in [95] to improve the reactive power sharing in case of a mismatch of line impedance. The accurate response can be achieved within 0.01 seconds. A DRL based control method has also been proposed in [96] to coordinate the current sharing and effective voltage restoration for an islanded microgrid. In multiple case studies, considering overloading, communication line switching, and DER unplugging, the proposed system converges to equal current sharing for all DERs within 10ms and voltage is restored quickly.

Since the centralised primary control requires high bandwidth control loops, thus makes it infeasible for distantly located sources [15]. A microgrid with multiple ESs can also be controlled at a primary layer considering the definite SoC layer of all the ESs. For microgrid integrated with HEVs, the control system needs to acquire the charge efficiency/charge acceptance close to 100% though it varies with respect to SoC [97]. At a low SoC, the charge acceptance is near 100% but it gets progressively poor when SoC is above 80% [98]. To coordinate and manage multiple units there will be a requirement of monitoring the SoC layer by using appropriate sensors and the communication infrastructure so that the output power of the batteries can be regulated. Specifically focussed on the DC side of the microgrids, the SoC-based power-sharing strategy has been developed by connecting all the energy cells to a common bus with power electronics-based interfacing converters and the virtual impedance value depends upon the value of SoC raised by an exponent [99]. However, there is a trade-off between the accuracy and the voltage deviation with this approach which is tried to alleviate in [100] by introducing fuzzy logic control but analysed only on a single system. Fuzzy logic based mechanism fine-tunes the droop coefficients of local controllers in the primary layer to maintain the SoC level among all the storage devices. It improves the primary control but the steady-state error can not be eliminated by this method. In the continuation, authors in [101, 102] proposed a similar fuzzy logic-based decentralised control for balancing the SoC of multiple energy storage units and since all the units are self-controlled and managed oneself without the need of any communication system, the approach promises the high scalability in microgrid environment. Fuzzy logic seems a good alternative for droop control but sudden charging and discharging for power-sharing can impact the energy life and its overall performance [20]. Furthermore, it can also result in reduced power handling capability of the complete system. Keeping this in mind, a constant bus voltage scheme has been proposed in [103] based on energy-ultracapacitor hybrid storage system where fuzzy logic controller is designed in such a way that it will maintain the bus voltage stable with the help of ultracapacitor and control the power flow from hybrid system to the rest of the microgrid. The peak to peak DC voltage deviation in case of undershoot improves from 45.7 V to 47.2 V and it improves from 51.3 V to 49.2 V in case of overshoot.

Online estimation and prediction of SoC by AI-inspired techniques can improve accuracy. For example, the NN-based estimation model can improve the SoC estimation with an average accuracy of 3.8% [104] and their integration with individual local controllers can improve the overall control structure in microgrids. The efficient learning capability from the historical data and prediction with high accuracy leads to better controllability [105]. State-of-the-art approaches using neural networks for SoC estimation have been developed in [106–107]. Authors in [108] have estimated the SoC using data-driven FFNN based method by establishing the relationships among the energy characteristics like current, voltage, SoC, temperature and polarisation state. Considering all the characteristics, the FFNN based SoC estimation method keeps the error to the lowest and within 2%.

4.1.2. MPPT control

The MPPT controller enabled with the NN based framework can give improved and reliable results [109]. Recent research in [110, 111] have adopted a radial basis function network consisting of a single neuron (SN-RBFN) integrated with a PI controller. The single neuron approach has also been implemented in [112] considering the weight initialisation for the backpropagation algorithm. RBFNN controller provides an estimated tracking error MSE (mean square error) of 0.0004 and takes only 4 ms to reach steady-state with negligible fluctuations[110]. In the case of variable irradiance and wind speed, the SN-RBFN algorithm achieves MPP within 38 ms compared to the standard incremental conductance algorithm that takes 92 ms[111]. Integral Absolute Error (IAE) and the Integral Time Absolute Error (ITAE) with direct neural control method are 0.216 and 0.0157 respectively compared to 2.593 and 0.3321 respectively in the case of the P&O algorithm [112]. Authors in [113] have proposed a similar approach with an increased number of layers and inputs as panel temperature, output voltage and current of PV. Further, step changes in irradiance, temperature and load have been applied to the model to present the advantages of adopting RBFN over traditional fuzzy logic controllers. For example, improvement in average output power by 14.89% has been achieved with RBFN compared to perturb and observe (P&O) method. A general regression neural network (GRNN) model is devised in [114] to find the MPP using the modified P&O method and particle swarm optimization (PSO) algorithm. It brings advantages like execution time reduced to 10.68s compared to 38.28s in the P&O method and increment in average power output by 15% compared to the P&O method. The above-discussed techniques are still partially driven by the model-based designing approach. There is still enough scope for researchers to explore and develop the data driven models that will reduce the need of exact system information and help in achieving the improved performance.

4.1.3. Inertia estimation and control

Decreasing inertia in microgrids is one of the major concerns to maintain system stability [115]. Various studies [116–117] have been done to introduce virtual inertia control but they lack model-free optimal control. Reinforcement learning (RL) techniques have been emerged in recent years to address the above-mentioned issues. An NN-based heuristic dynamic programming for virtual inertia control is proposed in [118] for grid-tied inverters. For non-inductive grids, the NN adapts variable impedance angle and the dynamic programming with actor-critic framework facilitates the self-control to different changing conditions in the systems. Comparative study shows that conventional PI controller doesn't function properly as it requires reactive power to regulate the magnitude of inverter output whereas NN based controller updates the network weights during online training and regulates the inverter output with minimum fluctuations. Authors in [119] have presented a dual heuristic dynamic programming that includes the neural network, actor and critic network. The former network improves the performance against uncertainties like changing rotor angles etc. and the later network optimise the cost function associated with it. The simulation shows that the proposed approach improves the tracking ability of inverter output to control active, reactive power and frequency stabilisation compared to the traditional PI-based controller. Researchers in [120] suggest the NN-based adaptive controller that facilitates the online training to automatically adjust the setting of the controller according to the instantaneous system's parameter values. The RL-based heuristic dynamic programming then provides the optimal control of power and frequency regulation in the grid-tied microgrid system. In contrast to the DHP method, authors in [121] present an RL based deep deterministic policy gradient (DPG) optimisation algorithm to provide the frequency stability in the system. The proposed virtual inertia controller works better compared to H_∞ and PI controllers. The integral absolute error with inertia and no inertia control case in NN-based controller is 28.4136 (lowest) compare to 28.4461 and 28.7557 in H and PI controller respectively. A recent work [124] in a similar area follows a model-free faster convergence decentralised DPG algorithm that finds the optimal control policy needed to control the active power, frequency stabilisation during the transient process. The observed frequency disturbance is less after fault transients and load disturbance compared to the grid following and droop converter control.

4.2. Secondary control

The secondary layer mainly controls the deviations that occurred in voltage and frequency caused by the primary control. In general, the secondary control with conventional methods has a lagging response, inaccurate controlling issues and requires extensive communication infrastructure [123]. Improper communication can affect the synchronisation of all the units in the microgrid and system reliability will be at risk which must be alleviated. Network-level protection and microgrid stability during faults is also a challenging task at this layer of control [124] and therefore intelligent control techniques must be implemented to deal with these issues. The following sub-sections provide the review on classical and AI implemented techniques with future prospective.

4.2.1. Voltage and Frequency deviation control

At this layer, the controller must maintain the fluctuations that are not controlled at the primary layer, within the acceptable limits for any change in load or generation [125]. Authors in [126] propose a solution to mitigate the voltage unbalance for the islanded microgrid, realised by sending the control signals to local controllers connected at the primary layer. Centralised secondary control for islanded microgrid has also been presented in [127] where voltage and frequency deviations are restored while maintaining the appropriate sharing of reactive power. However, these control measures are effective but the increase in ES assets in the microgrids bring complexity in controlling and thus raises concern. Considering the contribution from ES, novel works have been presented for secondary stage control examining the SoC and minimising the deviations under this control layer. In this trend, an SoC based droop control has been employed in [128–129], where ES with higher SoC delivers more active power and the unit with lower SoC generates less. The conventional droop control is promising but often suffers from small-signal instability problems [130]. Going on with the latest technology, the ML inspired models can solve the system dynamics complexity effectively even with no or partial dynamics information being available in advance [131].

To overcome the issues of voltage and frequency disturbances, NN-based model has been deployed in [131]. The developed multilayer perceptron (MLP) model considers the parameters based on system dynamics, including linearity and non-linearity aspects of the controller. Results demonstrate good overall system stability, however, the system considering a synchronous generator with multiple DERs and loads, is yet to be examined. The MSE of voltage and frequency deviation is approximately 50% and 40% less respectively compared to the PID based controllers. Authors in [132] used ANN and Genetic Algorithm (GA) to control the voltage and frequency deviations at the secondary layer. The inclusion of GA optimization at this stage allows parameter initialisation and ANN facilitates the online tuning of parameters and faster prediction of changing system dynamics. The work here considers the islanded microgrids with limited DERs and loads, thus scalability and operation in grid-tied connection mode will remain the area of exploration. Authors in [133] have proposed a novel reinforcement learning (RL) algorithm to compensate for the reactive power, unbalanced load currents and harmonics. RL provides an online learning environment where the secondary controller can take instantaneous possible actions based on parameters crossing the safe operational limits. Furthermore, the developed system has been tested on different scenarios such as load change, unbalanced load conditions, non-linear load switching and the three-phase fault condition. However, the validity of the RL based approach while including impacts of ES is not explored. Researchers in [134] have proposed a novel DRL based interval type 2 (IT2) fuzzy system especially focusing on load frequency regulation. IT2 fuzzy logic controller (IT2-FLC) was designed since conventional FLCs cannot handle linguistic uncertainties in unstructured environments. Thus, the self-tuning and adaptive learning capability with improved controller action make the overall system effective against frequency regulation in the microgrid. However, it is developed only for islanded microgrids. The frequency deviation in case of load disturbance with a conventional controller is 0.0249 Hz while the same with the proposed controller is 0.0163 Hz.

A distributed ML technique has been proposed in [135] at the secondary layer voltage control for islanded microgrid without the need for a communication channel. A cluster-based unsupervised model has been developed considering the data availability from PV, wind, load, and the sudden load change events. Researchers in [136] have proposed a noise resilient cooperative secondary control for a multi-agent system. It considers the complete non-linear model of the system and noisy measurements. These techniques can also be validated for DC and/or hybrid microgrid structures. In case of small and large-signal disturbances, the proposed control scheme restores the voltage and frequency fluctuations to maintain stability. NN based secondary control for voltage regulation and current sharing in DC microgrid is proposed in [137] that utilises game theory and adaptive dynamic programming to manage current sharing and regulates the DC voltage without the need of an accurate model of a microgrid. An RL is introduced in [138] for controlling voltage and frequency deviations at the secondary layer control with penetration of wind generators. Q-learning (referred to as RL) is adopted here to develop a model-free mechanism that efficiently captures the system non-linearities and controls the frequency and voltage fluctuations by agents assigned to them. NN-based short term LSTM forecasting technique has also been adopted in [139] that forecast the generation and demand in near real-time and the controllers. It helps to maintain the DC link voltage balancing the SoC level instantaneously.

An extreme learning machine (ELM) [140] is another interesting and emerging NN algorithm. This algorithm resolves the slow learning speed problem of FFNN by enabling a single-hidden layer FFNN that randomly initialises the input weights of neurons and determines output weights analytically. It provides the best generalisation at a very fast speed for NN-based models. Results show that SVM takes about 12 hrs for training the model on given input samples, whereas ELM does this only in 1.5 minutes. An ELM embedded technique is proposed in [141] where a consensus-based secondary control regulates the voltage through a communication network for effective power-sharing. The loss of data in the transmission is handled by ELM that predicts the lost voltage and the control unit is activated to bring the operating point to that forecasted voltage and thus the voltage regulation is achieved. An adaptive DRL-based secondary frequency control has been proposed in [134] considering the tidal and vehicle to grid unit in an isolated microgrid. The suggested method controls any power fluctuation and load disturbance and regulates the frequency. A data-driven and distributed heuristic dynamic programming based secondary controller is also presented in [142] that does not require accurate model parameters. The proposed framework is well adaptive to load disturbances and regulates frequency quickly maintaining the accurate active power sharing among all DERs.

4.2.2. Mitigate communication delay

Reducing communication delay is an important requirement in a hierarchical control structure. A robust communication featured secondary control is proposed in [143] in which a communication compensation block has been developed to deal with time delays and non-idealities in the communication network. An RL approach has been presented in [144] which is based on a resource allocation scheme, namely, delay minimisation Q-Learning (DMQ) that learns from the macro and small cell base stations at every time-to-transmit interval (TTI). The latency in communication is reduced by 66% and 33% compared to proportional fairness (PF) and Distributed Iterative Resource Allocation (DIRA) algorithms respectively.

A regression model for communication compensation is discussed in [143] that can guarantee the fast frequency and effective voltage restoration in any communication impairment environment. Due to more accurate prediction capability, this solution can restore the voltage in worse cases even with 60% data loss condition, which is also not possible by any conventional controller. A deep learning-based secured communication network is proposed in [145]. Emphasis has been given to cyber resilient communication networks by enabling detection and classification of unusual signals through Fast Fourier Transform (FFT) and training the deep learning model with extracted coefficients. The results have shown 99.35% accuracy in detecting the false injected signals and the operation of the microgrid was unaffected in these circumstances. The summary of different communication-based controllers with their main contribution is plotted in Table 4.

4.2.3. Protection & effective fault restoration

Post fault system stability is a crucial technical problem in the microgrids embedded with low inertia systems. The stochastic and intermittent nature of DERs further advances this stability issue. Any short circuit fault during contingency can introduce oscillations in the power system which would ultimately result in voltage fluctuations. Corrective Voltage Control (CVC) must be placed to maintain stability by controlling active and reactive power dispatch from the DERs and preserving sufficient load margin. Authors in [151] present an ML-based secondary layer CVC framework wherein a feature selection technique follows an online-offline data analysis that contains the fault location, stochastic cluster and sensitivity feature and is then fed to the ANFIS model. The model predicts the optimised active and reactive power from each of the DERs to further restore the voltage. This work considers the

Table 4
Research work related to communication infrastructure control in microgrid

Main contribution	Controller type	Complexity	Implementation of AI	Ref
Delay margin calculation	Gain scheduling	Low	×	[146]
State estimation	Non-linear	High	×	[147]
Stability analysis	PI	Low	×	[148]
Stability enhancement	PI	High	×	[148]
Time delay model	MPC	Low	-	[149]
Optimisation information sharing	Adaptive	High	×	[150]
Communication compensation	Regression-based	High	✓	[143]
Low latency communication	RL based	High	✓	[144]
Cyber resilient communication	FFT & NN based	High	✓	[145]

induction generator based wind turbine in a grid-connected microgrid system. In future, the performance of AI-based CVC could be done in presence of ES in microgrids. An SVM based fault detection method has been described in this method that measures the voltage and current at each of the selected. If a fault exists, then the DG nearest to the fault injects harmonic at a correctly selected frequency and the impedance seen at this point is measured and sent to the SVM classifier to detect the accurate location of the fault section. A similar approach has been discussed in [152] that concludes the FFT and SVM for effective classification and detection to control the system stability in an islanded microgrid. The minimum average error in fault localisation for the longest line in IEEE 34 bus system was found 0.0012 and 0.0021 for clean and noisy data respectively. Another tree-based ML model has been proposed in [153] that follows the principle of measuring voltage and current signals at each feeder and FFT identifies the sensitive features followed by the ML model that extracts the faulty events and informs the control system to take necessary actions.Recently, NN-based adaptive protection of microgrid is also presented in [154] that combines basic features of ANN and SVM both. For the fault identification, ANN shows almost no error whereas SVM shows errors within 0.25% for faults on different buses.

A multi-agent-based ML model has been developed in [155] for the protection of AC microgrids in both grid-tied and islanded modes. After training the ML model from the collected fault data, the KNN algorithm is used to classify the particular fault and on the occurrence of a fault, multiple agents start communicating to coordinate and segregate the fault. Results show that the proposed work can provide primary and backup protection in grid-connected and autonomous microgrids. A summary of AI-based primary and secondary control methods in DC and AC microgrids is tabulated in Tables 5 and 6 respectively. Both tables summarise the finding based on some other important aspects, such as (i) system control strategy, (ii) grid connectivity and (iii) validation level. Table 5 shows that the DC microgrid researches are mainly for off-grid conditions, more focus has been given to voltage stability and power-sharing controls in a distributed control architecture. NN based solutions have been mostly practisedfor control in DC microgrids out of which two solutions are validated in real-time experiment environment.

Table 6 shows the findings for AC microgrids. Centralised and distributed architectures are mostly considered. NN based solutions have been mostly practised and only one solution is validated in real-time experiment. Similar to DC, AC microgrids are also considered mainly in off-grid conditions. Hence, grid-connected conditions and implementing AI in islanding detection and reconnection mechanism should be focused on.

Table 5
AI-based Primary & Secondary control in DC microgrids

Control strategy	AI Technique	Objective	Grid connect (Off/On)	Ref
Centralised	ANN*	Power sharing, Voltage regulation	Off	[94]
Decentralised	ANN	Voltage stability, Power sharing	Off	[91]
Distributed	DRL	Voltage restoration, Load sharing	Off	[96]
	MLP	Frequency and voltage stabilisation	On	[131]
	BPNN	Current sharing, voltage regulation	Off	[137]
	LSTM*	Maintain SoC level and voltage stabilisation	Off	[139]
	NN	Classify and detect cyber attacks	Off	[145]

All are validated in simulation mode. * validated in real-time experiment

4.3. Tertiary control

The top layer in the hierarchical control scheme, tertiary control operates for the tasks associated at the distribution/networked level. The tertiary layer manages the optimal power flow within microgrid units and also the power import/export from the external grid. Therefore, it is an essential control layer to coordinate and ensure the economical and optimal power dispatch from each DER unit minimising the operational cost [158]. Further, energy market-related operations also come under this control which allows the DER units to participate in the energy market and also provide grid support services to other microgrids/ external grids in the vicinity. The implementation of AI-based techniques can accelerate the research to find solutions to deal with control issues associated with this layer which have been discussed in the following sub-sections.

4.3.1. Optimal economical operation and power flow management

The optimal power flow (OPF) problem solves the optimum objective function value for the electrical network with given constraints like network power quality requirements, asset operational limits. For a simple DC power flow based objective function, OPF can be a convex optimization problem. For the AC power flow, OPF is a non-convex problem making it computationally challenging and approximate or

Table 6
AI-based Primary & Secondary control in AC microgrids

Control strategy	**AI Technique**	**Objective**	**Grid connect (Off/On/ Both)**	**Ref**
Centralised	FFNN	Power-sharing Droop control	Off	[90]
	ANFIS	Reactive power-sharing	Off	[95]
	MLP	Frequency response	Off (multi-microgrid)	[156]
	ANN	V/f regulation	Off	[132]
	ANN*	Frequency regulation	Off	[134]
Decentralised	SLFN	Power sharing	Off	[141]
	-	Communication delay	On	[144]
	RL	V/f regulation	On	[138]
Distributed	ANN	V/f regulation	Off	[135]
	ANN	Frequency regulation	Off	[142]
	ANFIS	V/f regulation	On	[151]
	—	Frequency regulation, power-sharing	Off	[157]
		Data prediction	Off	[143]
Not mentioned	ANN	V/f regulation	Off	[118]
	ANN	Optimalcontrol	On	[119]
	ANN	Frequency regulation	On	[121]
	ANN	Optimal control	On	[122]
	—	Power quality	On	[133]

All are validated in simulation mode. * validated in real-time experiment heuristic methods cannot guarantee a globally optimal solution [159]. The OPF is generally solved for the steady-state network conditions. However, a dynamic OPF (DOPF) [160] can be implemented at the tertiary layer control in a microgrid setting with ESS such that the power output of DERs can be optimally coordinated for a given time horizon. Despite some optimization relaxation, studies in [161, 162] have not considered the line losses, voltage and reactive power flow limits. Non-convex optimization problems for the power system considering the microgrid enabled with ES is presented in [163] mainly responsible for dispatchable (on/off) decisions for DERs. Further to its extension, a stochastic optimization approach has been adopted [164] for model convergence and feasibility guarantee. Recursive dynamic programming [160] can also be used for the same.

A dynamic programming based predictive control approach is presented in [165] for the power flow management in a grid-connected PV with ES for peak shaving as an objective function to maximise the owner's profit. A similar approach has been considered in [166] with added market participation feature but the forecasted PV profile has not been compared with actual values and the errors (RMSE, MAPE) are not calculated to see the accumulated impact on overall revenue. Also, the focus should be given to reactive power management which is of great importance during power exchanges with the main grid. A multi-objective optimization problem for an isolated microgrid containing diesel generators, wind turbines and an energy storage system is proposed in [167] to maximise the power flow balance capability and minimise the fuel cost related to diesel generators and energy life. To solve the multi-objective function, a weighted sum method is chosen where the weight for the individual function is chosen arbitrarily. The DOPF strategy for a microgrid with a single storage system or aggregated storage has been presented in [168, 169, 170] focusing only on the power exchanges between the microgrid and the main grid. Authors in [171] have presented an optimal power exchange operation in a networked microgrid environment with an emphasis on minimising the power purchase from the main grid. This operation with the centralised control scheme will require robust and reliable communication infrastructure.

Data-driven methods with emphasis on ML techniques to solve optimal power flow have been presented in [172, 173] and has proved to be efficient enough to address the technical challenges associated with DER uncertainties and voltage regulation. A data-driven based OPF solution for multiple DERs is presented in [174] that learns the control policies associated with each DER to impersonate the solution to a centralised OPF from exclusively local information. This approach requires no manual controller tuning and little or no real-time communication. Authors in [173] have proposed a decentralised, real-time method for optimal dispatch of DERs that avoids the extensive remote monitoring and communication infrastructure. This decentralised control can manage very well the short-term voltage violations as compared to the existing local control schemes. Further to its extension, an optimisation control scheme for a network operation featuring active power curtailment, reactive power control, controllable loads and storage systems is presented in [172]. It considers a data-driven local control design for multiple DERs and an offline centralised control algorithm for solving the optimal power flow problem. Compared to the conventional control scheme, the proposed method increases the power flow efficiency by 4.45%. Voltage and current limits are also within the acceptable grid codes. A DRL based decentralized optimal control strategy for a hybrid storage system in a hybrid AC-DC microgrid has been devised in [175] that efficiently deals with the power quality disturbances due to the charging and discharging of the ES and manages the complete system in both grid-connected and islanded modes. It allows a smooth charging process and negligible disturbance to the bus voltage. Moreover, the RL based method efficiently deals with the system mismatch error between hardware experiments and software simulation.

A cooperative RL is proposed in [176] that coordinates the multiple agent actions for optimising the economic dispatch from DERs. The solution is applied in a residential microgrid with a 33-bus distribution feeder and demonstrates a guaranteed lowest cost solution for load dispatch among participating DERs. It reduces the dispatch cost by at least 10% lower than the scenario-based algorithm. Researchers in [177] have presented an NN-based EMS for a grid-connected microgrid using a multi-agent system to reflect and adapt the dynamic characteristics of various generation units in the microgrid. Agents have been assigned to the wind, controller, load, storage units and main grid to coordinate and reduce the amount of power imported from the grid to minimise the cost and maximise the benefit. Especially the proposed algorithm gives the lowest MSE of 0.70826 for predicting wind speed, The predicted data then is utilised to control ESS and balance the cost and benefit in a microgrid. Supervisory control for wind farms integrated with an ESS has been proposed in [178] where an NN-based controller stabilises the power fluctuations in the system and also it can support the frequency response services on the whole system. An energy flow scheduling in the grid structure with active prosumers has been discussed [179] in which the reference of NN and optimisation algorithms are implemented at the local layer to fast calculate the scheduling of units. The results show that the scheduling with NN and local optimisation is faster than the traditional genetic algorithm. A real-time EMS and control strategy in microgrid with deep learning-based adaptive dynamic programming is presented in [180]. The NN based training results show that the proposed method converges quickly taking only 16.533s and the convergence is close to actual values with an almost zero MSE. Thereby faster optimisation and real-time accurate control can be obtained. The researcher in [181] considers an NN-based architecture for an online EMS strategy to extend the storage lifetime and improve the efficiency of a hybrid storage system. The proposed controller improves the storage state of health and reduces the peak current demand by 15% and 60% respectively compared to the battery-only method. The hybrid solution and control help to improve the storage lifetime by 64.8% more compared to the battery-only solution. The multi-objective problem is solved by dynamic programming (DP) and the results are utilised to design the framework for training the NN so that the online control is made possible in real-time. An ANN-based decision-making algorithm is proposed [182] for real-time energy management in a vehicle to grid (V2G) connected system. Charging and discharging schedule classification is accurately predicted by ANN such that the cross-entropy and error percentage for the test data is only 0.012% and 0.69% respectively. It shows that the proposed method is very accurate and capable enough to schedule EV charging and discharging. A frequency control method is proposed in [183] using RNN enabled controller with optimisation achieved by the PSO algorithm. This method effectively controls the frequency deviations while maintaining the SoC level . With the ANN based controller, the maximum frequency deviation is 0.025 Hz while it is 0.028 Hz when simple low pass filter based controller is used.

A whole set of NN controllers is presented in [184] for different microgrid components that include grid power tracking, energy power tracking, PV and wind power tracking. The optimal power management for the entire microgrid is managed by linear programming which tracks the reference power from all the neural controllers. However, different variable conditions like wind speed, SoC etc. are not analysed in the paper. A power management strategy in a large scale power grid model with a wind-solar type energy system using the RNN approach is discussed in [185]. The proposed method works very well over the different number of nodes and randomness in the topologies. In the 1000 node system, there is an improvement of 61.86% occurs in the number of power shortages considering no rewiring probability. Researchers in [186] have described RNN based optimisation solution for a grid-connected microgrid to minimise the power import from the main grid and maximise the utilisation of DERs. The RNN determines the optimal power flow to manage the power required by EV, wind, solar, energy systems and loads. An extended Kalman filter-based neural network is trained to predict power demand, wind and solar power. The average mean square for predicting power demand, wind and solar power is 0.00065, 0.00186 and 0.0065 respectively. The forecasted data is then used to optimise the power flow. A similar control strategy based on RNN is discussed in [187]. The methodology utilises RNN to model and control ES considering SoC to manage the power flow among load, wind, solar and storage system. Despite fluctuations in DER output and power demand, the RNN based method accurately determines the battery size and reliably maintains the SoC level.

4.3.2. Autonomous market participation

Towards the decarbonisation of the power system network, the active participation of DERs in the energy market is very important. To do this, a systematic approach has to be adopted considering the layer of complexity associated with different microgrid units. Researchers in [188] have proposed two energy management algorithms for a microgrid to enable automatic energy transaction with the main grid. The first algorithm involves MPC with linear programming to efficiently predict the energy generation, demand and prices. The second algorithm integrates the RL to optimize the transaction decision based on instantaneous information available in the system. MPC based algorithm gives a $65.74 daily average monetary benefit while Risk Seeking RL algorithm provides a benefit of $77.14. An NN-based forecasting model is developed and an optimisation algorithm is proposed[189] to prioritise the scheduling of assets in the microgrids. The proposed ML-based algorithm has better results compared to the bin-packing algorithm. This area is still at the early stage of research and can be exploited better with ML-based algorithms.

Similar to Tables 5 and 6, AI-based control methods at the tertiary control layer have been summarised in Table 7. Considering the findings as shown in Tables 5, 6 and 7, it is clear that till now a good amount of research has been performed at tertiary control. AI-based solutions are getting more importance in analysing optimal power flow, energy management, market participation etc. Centralised and decentralised architectures have been mostly practised. Similar to primary and secondary controls, findings show that only one solution at the tertiary level has been validated in real-time experimental mode.

Table 7
AI-based Tertiary control

Control strategy	AI Technique	Objective	Grid connect (Off/On)	Ref.
Centralised	SVM	Economic dispatch	On	[172]
	ANN	Energy management	On	[178, 179]
	FCN	Economic dispatch	On	[190]
	DL	Energy management	On	[180]
	RNN	Energy management	On	[185, 186, 189]
	RNN	Energy management	Off	[187]
	RL	Energy trading	On	[188]
Decentralised	SVR	Power flow management	On	[173]
	ANN*	Power flow management	Both	[175]
	LR	power flow management	On	[174]
	FFNN	Energy management	On	[177, 182]
	FFNN	Energy management	Off	[181]
	Elman NN	Energy management	On	[183]
	RNN	Energy management	On	[184]
Distributed	ANN	Economic dispatch	On	[176]

All are validated in simulation mode. * validated in a real-time experiment

5. Networked microgrid

Increasing installations of DERs at the low voltage distribution network, of course, bring the advantages like lower energy cost, reduced emissions etc but in exchange for degrading grid stability and resiliency [191]. One of the effective ways to manage this would be connecting multiple microgrids and coordinating each element through a robust control mechanism [192]. Interconnected microgrids can provide support to each other and the external grid during contingency events. Interconnected microgrids exhibit a complexity to design the network as it contains several different units with a different set of objectives. On the broader perspective, based on interconnection architecture, microgrids can be divided into three categories [193]:

5.1. Parallel Connected Microgrids (PCM)

This architecture consists of a topology such that all the microgrids are connected to the same external grid, with each microgrid having its own PCC. This structure can work better in grid-connected mode and can facilitate ancillary services to the external grid. In case of main grid failure, the individual microgrid can go in islanded mode and there is a possibility of uncontrolled voltage and frequency deviations. So, a robust islanded control mode is essential. Research on this architecture is mainly found for MV distribution networks [194–195].

5.2. Grid Series Interconnected Microgrids (GSIM)

GSIM topology comprises several microgrids that are connected directly without the presence of any external grid. This structure should have strong coordination to control voltage and frequency deviations throughout to have resilient and reliable operation. However, any occurrence of disconnection will make the system to be split into subclusters and microgrids within the smaller clusters will still have some external support. In this way, the overall system can have better performance without external grid support. Authors in [196, 197] have studied this architecture but the potential benefits are still to be explored.

5.3. Mixed Parallel-Series Connection (MPSC)

Taking advantage of PCM and GSIM architectures, MPSC have the ability where microgrids can be connected to the external grid directly or can form a cluster of interconnected microgrids. Each of the clusters will have at least one interconnection with the external grid. Through this arrangement, microgrids can provide services to the external grid and looking at another way, the individual microgrid can also get support from the external grid [193]. The layout for the networked microgrids is shown in Fig. 4 and the comparison of these layouts with their advantages and disadvantages is summarized in Table 8.

5.3.1. AI in networked microgrid

The resilience support during the power system outages can be expanded by interconnecting/networked microgrids to provide the services to the main grid when it is not available for an extended period [191, 198]. The multiple microgrids can be connected to the network at the distribution level through one or more switches. However, the switching operations to connect/disconnect individual microgrids can cause uncontrolled frequency and voltage deviations that ultimately could lead to system collapse [199, 200]. Therefore, control measures are necessary to ensure safe and reliable operation, especially in transient periods. Primary layer control for frequency stabilisation is proposed in many works [201, 202, 199] that follows the manually tuned PI controllers, but can’t be a good solution for networked microgrids to manage multiple controllers [156]. Their stagnant control response to abrupt system disturbances and oscillatory behaviour are some other factors that motivate to find some innovative solutions.

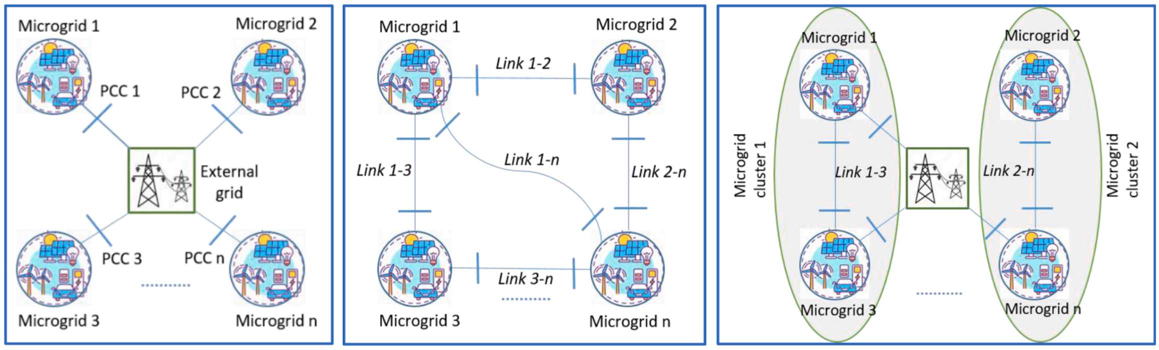

Fig. 4. Networked microgrid architectures, (left-to-right) a) PCM b) GSIM c) MPSC

Table 8
Advantages and disadvantages of microgrid clusters

Interconnection type	Control architecture	Advantages	Disadvantages
PCM	Centralised	Effective operation & control	High communication requirement
	Distributed	Lower communication requirement	Comparatively, less optimum control
GSIM	Centralised	Optimum operation possible, post-contingency event forms sub-clusters for isolated mode	High communication requirements
	Distributed	Comparatively lower communication infrastructure than centralised	Operation may not be optimum compared to central
MPSC	Centralised/ Distributed	External main grid support services possible	Extensive communication requirements and less effective optimal control
PCM/GSIM/ MPSC	Decentralized	N/A	Not recommended [54]

An NN-based tuner can be deployed as a supplementary control system that will adapt the dynamic system state and take control actions accordingly [203, 204]. It improves the performance, however, it increases the controller's response time which should be addressed properly to achieve the fast-acting control system. To mitigate these issues, an RL-based policy approximation algorithm utilising the deep NN-based system model to perform efficiently in various switching possibilities in a multi/networked microgrid environment is proposed in [156]. RL based controller improves the performance with almost zero overshoot and steady-state error. This model works on the conservative voltage reduction (CVR) method wherein the frequency is tracked by the RL algorithm.

A distributed secondary control of interconnected microgrids using multi-agent systems and the RL algorithm is proposed in [205]. This methodology can achieve global coordination in interconnected microgrids in a distributed manner and the voltage and frequency can be controlled effectively.

A concept of voltage and frequency control for islanded multi-microgrids using adaptive NN and distributed cooperative control has been discussed in [206]. Model-based controllers were designed using Lyapunov theory and the ANN predicts the system dynamics to control the parameters. A generation capacity optimisation using ANN is also proposed for the islanded operation of an incoming microgrid in a multi-microgrid [207].

The ANN-based EMS is presented in [208] where the ANN-based forecasted electricity demand and renewable generation from each microgrid are collected and the EMS schedules the storage duty cycles and facilitates the energy transactions among different interconnected microgrids. Operation and control of networked microgrids are experimentally demonstrated in [209] where the Gaussian process-based regression model forecasts the energy supply and demand for each microgrid followed by an MPC to optimise the grid operation considering the constraints.

Authors in [210] have presented a multi-agent-based transactive energy trading platform in an interconnected microgrid system focusing on ESS market models at the local and global layers. RL algorithm develops the bidding strategies. Multi agents are assigned to different units within each inter and intra-microgrid market and found that the ESS can trade energy and earn more benefits at local layer participation, however, ESS can be used to balance the energy mismatches effectively in a pool of microgrids.

The resiliency of interconnected microgrids has been studied in [211] by examining the real and predicted dynamic states of the system. Various factors like time-shifting, magnitude deviations and other data averaging effects were considered individually and later collectively to determine the power imbalances at a unit time step. The uncertainties are quantified and eliminated in the proposed power-sharing algorithm to develop an efficient EMS. In future, AI-based solutions may be considered to understand more realistic extreme weather conditions, develop forecasting algorithms, and implement other control strategies The AI techniques for interconnected microgrids are summarized in Table 9.

6. Discussion and future scopes

While it has been a common notion that microgrids are preferable to solve local problems and can support the pathway to decarbonise and self-healing grid of the future, control and management of DERs will remain the area of exploration. Previous sections review the progress on implementation of AI techniques in the control architectures with the

Table 9
AI techniques for networked microgrid functionality

Networked microgrid functionality	AI technique	Validation level	Ref
Frequency support services	Multilayer perceptron (MLP)-driven RL	Simulation	[156]
Voltage & frequency regulation	Multi agent & RL	Simulation	[205]
	ANN & cooperative control	Simulation	[206]
Generation capacity optimisation	ANN	Simulation	[207]
Energy management system	-	Real-time exp	[211]
	Distributed ANN	Simulation	[208]
Cost-effective energy transaction	Gaussian process-based regression model	Simulation	[209]
Transactive energy trading	Multi agent & RL	Simulation	[210]

existing strategies in microgrids.

In this review work, we have considered more than 200 published papers where 40 papers deal with conventional control and mostly review papers, 124 papers on hierarchical control in total and 23 papers where AI have been implemented in networked microgrids. Details breaking are shown in Fig. 5.

Fig. 6 depicts the control schemes in hierarchical and networked microgrids that have implemented AI techniques. The techniques are categorised in ANN, DRL, DNN and classical ML. ANN includes shallow NN with mostly feed-forward networks including MLP. DNN on the other hand includes deep NN where the number of layers is high. Classical ML includes traditional ML techniques such as SVM, SVR and tree-based networks. Some areas are least exploited in terms of utilizing AI techniques like energy trading, energy management in networked microgrids, inertia estimation in primary control, communication delay mitigation in secondary control and autonomous market participation in tertiary control. Deep learning is still missing for control applications in networked microgrids.

The key takeaway points along with the future scopes from the previous reviews are presented as follows:

6.1. Primary control

Voltage and frequency regulation, real-time power-sharing, MPPT control, inertia control are the fundamental tasks at the primary layer. The traditional methods of control lack accuracy, speed, robustness and model complexity, therefore. The AI has emerged as a supporting tool that enhances the existing control operation and brings the model-free system design with higher speed, accuracy and lower computational cost. Local controllers can work efficiently if they are provided with some intelligence. NN and RL-based models at this layer have shown better performance for MPPT control, SoC estimation and voltage regulation over traditional methods. NN-based machine learning techniques have been implemented for voltage & frequency regulation and MPPT control. Key points:

1 Data-driven approaches are still at an early stage and should be further explored for MPPT control schemes, SoC estimation, battery health monitoring and ESS modelling especially for Li-ion batteries rather than just depending on their equivalent circuit and physics-based models [212]
2 For control at the primary layer, there are plenty of open datasets [212, 213] available to train the ML models but the quality of data is very crucial. Generalised data pre-processing techniques like initial data identification, consistency examination, invalid and missing data identification, data imputation and resampling, data verification, aggregation and statistics must be applied to improve the value of the dataset.
3 There is a lack of data available for the inertia estimation at the distribution network level. Especially regarding community-based microgrid solutions, inertia becomes very important to provide frequency response services and other islanding conditions. Inertia information available at low voltage microgrids will enable distribution system operator (DSO)/aggregator to better facilitate services within the low voltage network zone.
4 Traditional model-based droop control, PID based MPPT control and master-slave power sharing control have been deployed extensively so far but lacks accuracy and cannot adapt the uncertainties in a dynamic microgrid environment.
5 However, most of the research work done so far is limited to computer simulations. Real-time experimental validation and demonstration in a real-life environment are still the stringent requirements for enabling the technology to be fully commercially viable and transferring the advantages of technology to the real world.

6.2. Secondary control

Voltage and frequency deviation compensation and synchronisation of various units in the microgrid are essential tasks at this layer of control. PI-based control has been implemented in many research work to compensate for the deviation, power-sharing and harmonics. Real-time management of deviations requires automatic online controller tuning that learns from the dynamic system environment. Traditional methods are not efficient enough to control multiple DERs in the microgrid environment. Key points:

1 Too much lag in the communication channel at the secondary control can result in a rise in voltage and system oscillation which

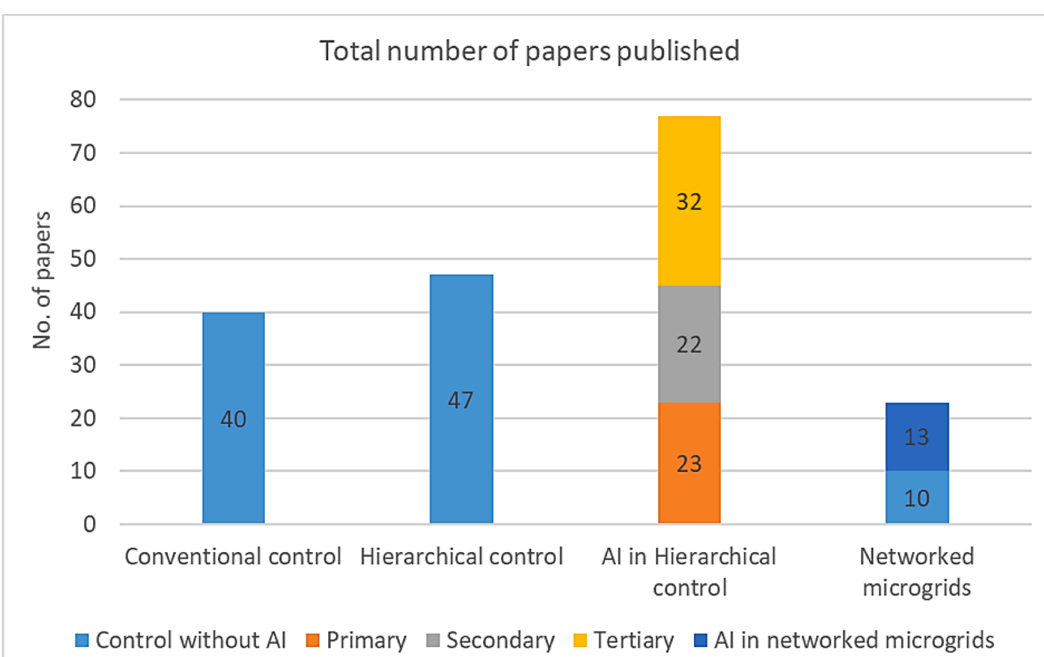

Fig. 5. Total number of papers published

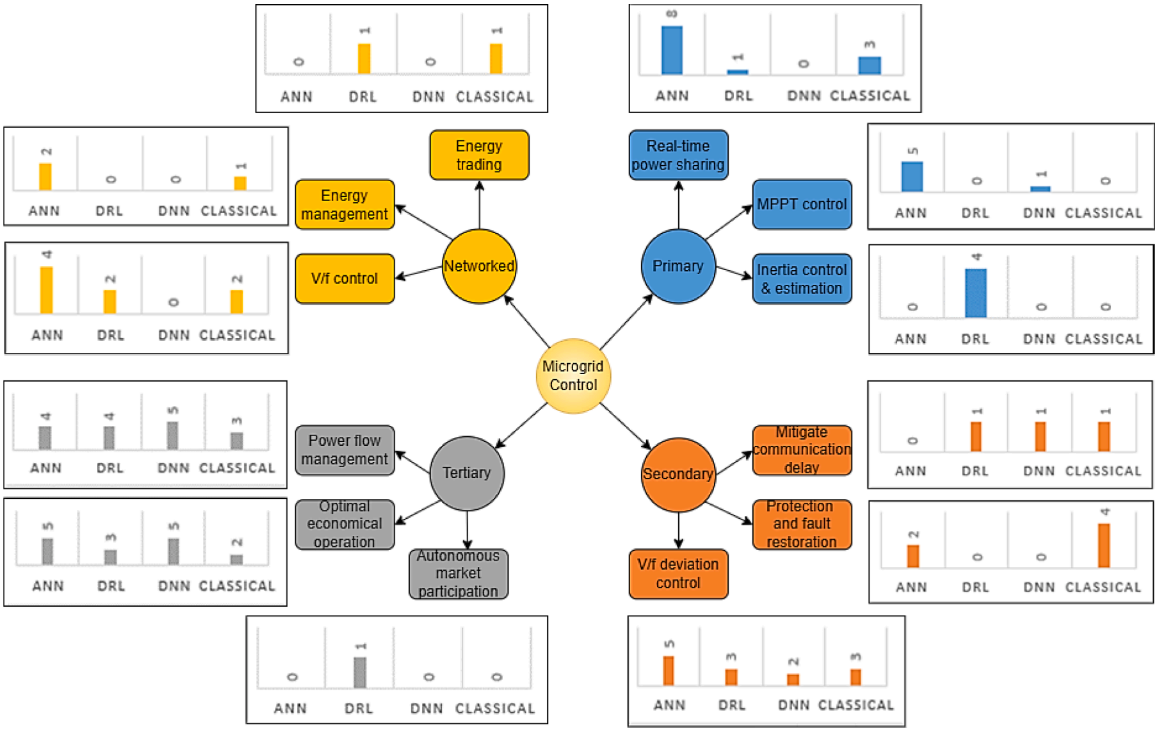

Fig. 6. Overview of the number of publications that implemented AI techniques in different microgrid control segments

consequently leads to degradation in power quality [214]. To coordinate multiple units, it is essential to have a robust communication infrastructure that comes with additional cost and complexity.

2 Multi-agent based RL solutions have shown positive results in reducing communication complexity. A little research has been done in this area and more investigations are needed in the real-time/real-life demonstration setup.
3 ML-based unsupervised learning also contains enormous opportunities to address the control issues at this layer. Classification and clustering, which fall under unsupervised learning can efficiently deal with the issues like power quality disturbance detection, fault detection and classification.
4 Autonomous market participation is very much less investigated area and in the era of high uptake of DERs at the distribution level, implementation of AI-based techniques (ANN and DRL) can ease the seamless market participation.
5 While most of the research focuses on making the microgrid self-reliable, the benefits of providing grid services should not be neglected and the appropriate control using AI must be developed.

The future opportunities of implementing AI techniques in the specific hierarchical control layers and their link with the conventional control methods are recapped in Fig. 7.

6.3. Tertiary control

Network and external grid-level interactions are controlled and managed at this layer. Economic load dispatch and power flow management within the microgrid and with the external grid are the essential tasks that must be performed reliably at all times. This layer requires extensive information on all the assets involved in the microgrid operation to ensure the safe and reliable operation of the system. Traditional controllers use complex programming which makes the execution time longer and faster convergence is not easily realisable. Key points:

1 Data-driven ML techniques can efficiently deal with the convergence problem by eliminating manual controller tuning and negligible communication infrastructure.
2 Cooperative agent-based DRL has shown good results to coordinate the multiple agent actions and availing the economical load dispatch. Moreover, it is easy to model variable DERs by assigning them unique agents based on their characteristics and cost-effective energy transaction can be achieved.
3 For continuous action and decision process especially in energy management with market participation, value-based RL may not be suitable and policy-based actor-critic framework method could be explored [215, 188].

6.4. Networked microgrids

Interconnected microgrids can effectively support each other and the main grid in the event of contingencies. Three networked microgrid architectures have been studied in this paper namely, PCM, GSIM, and MPSC. Despite, these architectures are bringing a level of reliability in the system, the control and coordination in the networked microgrids are difficult as each of these contains more microgrids and each unit has different requirements. There has not been plenty of research done in this area yet some AI-enabled techniques have been reviewed in this paper and key points are:

1 Because of the diverse entities involved in multiple microgrids, Co-ordination among them is a cumbersome task. To deal with this issue, hierarchical RL solutions could be explored which autonomously decomposes the complex decision-making tasks into simpler tasks [176].
2 For the data generated in local microgrid and/or global network of microgrids, a common decentralised or distributed framework will be required to utilise the data along with data privacy and the lowest latency in communication.
3 DNN is not explored in networked microgrids. One of the reasons could be the complexity in tuning the hyperparameters. To deal with this issue, hyperparameters auto-tuning algorithms like Gaussian

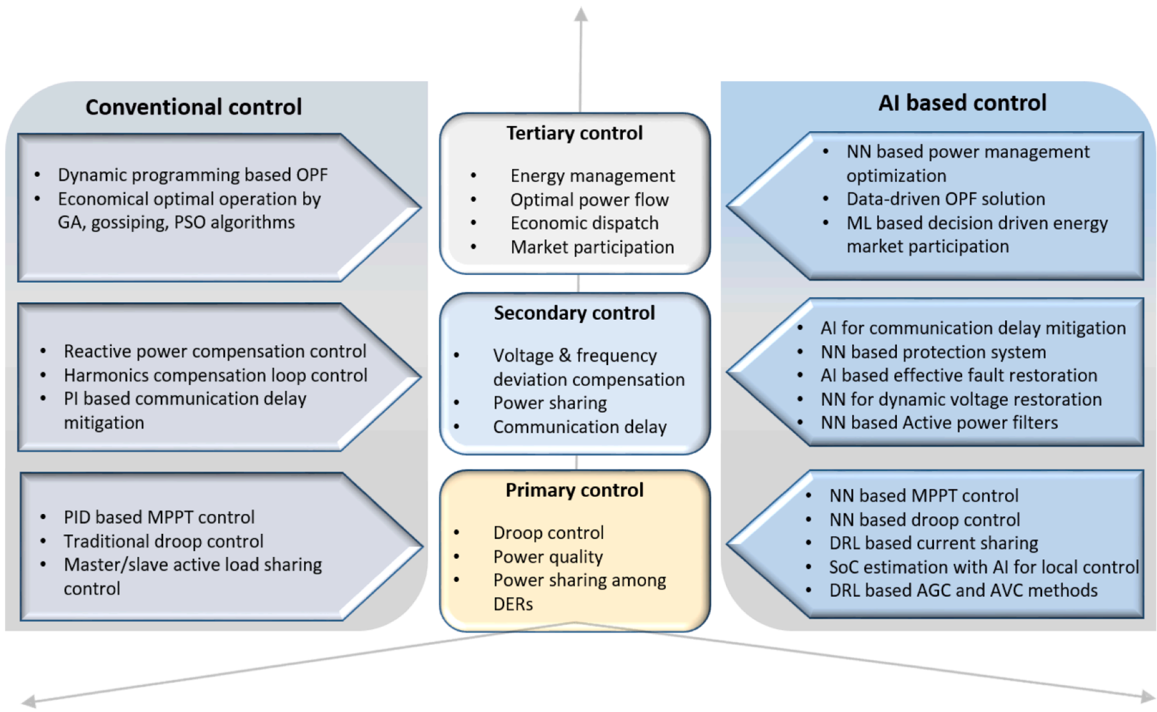

Fig. 7. Conventional and prospective AI-based control in the hierarchical control architecture

process-based bayesian optimisation and tree parzen estimator could be used.

4 RL is implemented for voltage and frequency control but with very limited functionalities for market-based energy transactions in networked microgrids. This area should further be explored for transactive energy markets with respect to ancillary services provision in networked microgrids.

5 Future research work in networked microgrids should focus on effective and intelligent power-sharing services, optimal power management, and autonomous market trading considering AI-based techniques.

6.5. *Trustworthiness of AI*

These days implementation of AI is getting more importance in almost all sectors. Extensive researches are being carried out on different AI techniques. In most cases, AI-based solutions are not yet demonstrated in real-life environments. Hence, the authors would like to draw attention to the trustworthiness of AI. Autonomous systems based on AI comprise complex algorithms and models. These models are built in a way so that they continuously learn from the new data coming into the input pipeline. Large dependency on data, algorithm complexities and the likelihood of unexpected behaviour of these AI-based systems necessitate the methodologies and framework that can guarantee explainability, transparency, technical robustness, nondiscrimination and fairness, privacy and accountability. These characteristics are crucial to understanding and establishing trust in AI-based systems [216].

For AI explainability, two types of approaches can be classified. First, explainable modelling or model interpretability, where the model itself is designed in such a way that the user can easily understand the mechanism of how the model is working internally. Second, Post-hoc explanation, which follows the model and can provide insights without knowing much about the internal mechanism of model working (e.g. by showing feature importance) [217]. More researches are needed to properly investigate the black-box behaviour of AI-based systems and make them transferable and explainable. The development of data-driven and knowledge-driven hybrid models for feature engineering is another promising research area to enhance interpretability. It is evident that the usefulness of AI explainability is still missing in practice and supporting measures must be taken to create the trustworthiness of AI models (e.g. reporting and improving data quality, analyzing extensive validation and performance).

7. Conclusion

This paper provides an overall review of AI-based control in microgrid environments. An overview of existing traditional control methods, their drawbacks, the need for AI techniques and their implementation at the different levels have been reviewed and future scopes have been presented. Despite system model complexities and challenges, it is found that AI can certainly be an important tool to enable the seamless integration and control of DERs at the local and networked levels. NN-based models are getting more focus on all levels. Most of the implemented AI techniques are physical model-based, whereas data-driven techniques should also gain more interest. Since a data-driven model doesn't require extensive physical system information, the design becomes less complex. However, in some specific applications like inertia estimation in the primary control, there is a lack of data available at the low voltage distribution network level. As ESS is becoming a core part of decarbonising the smart and microgrid networks, the datasets for ESS SoC levels which are accessible and open to the public require extensive preprocessing to improve the data quality and better predictability. Semi-supervised learning is not currently in practice for the microgrid domain and can be utilised where the available dataset is not totally labelled. In the secondary layer, communication infrastructure is another hurdle for smooth control. The existing research on AI-based communication focuses on RL based techniques that have been implemented to mitigate the communication requirement but more research should be done to reduce the complexity of model development. In the tertiary layer, autonomous market participation is also a less researched area and multi-agent-based RL can be implemented in future work. DNN-based solution has not yet been considered in networked microgrids. Validation of the developed/proposed solutions for single or networked microgrids environments in the real-time or real-life environment should also be focused on.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work is part of MiFIC project of IERC and Go-P2P, is a Task of the Users TCP by IEA. The authors in IERC thankfully acknowledge the support from the Department of the Environment, Climate and Communications and the Sustainable Energy Authority of Ireland.

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