Control and estimation techniques applied to smart microgrids: A review

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Abstract

The performance of microgrid operation requires hierarchical control and estimation schemes that coordinate and monitor the system dynamics of the process within the expected manipulated and control variables. Smart grid technologies possess innovative tools and frameworks to model the dynamic behaviour of microgrids regardless of their types, structures, etc. Various control and estimation technologies are reviewed for developing dynamic models of smart microgrids. The hierarchical system of a microgrid control consists of three architectural layers, primary, secondary and tertiary, which need to be supported by real-time monitoring and measurement environment of the system variables and parameters. Various control and estimation schemes have been devised to handle the dynamic performance of microgrids in the function of control layers requirement. Firstly, control schemes in the innovative grid environment are evaluated to understand the dynamics of the developed technologies. Six control technologies, linear, non-linear, robust, predictive, intelligent and adaptive, are mainly used to model the control design within layer(s) regardless of the types of microgrids. Secondly, the estimation technologies are evaluated based on the state of variables, locations and modelling of microgrids that can efficiently support the performance of the controllers and operating microgrids. Finally, a perspective vision for designing hierarchical and architectural control techniques for the optimal operation of intelligent microgrids is also provided. Therefore, the study will serve as a fundamental conceptual framework to select a perfect optimal design modelling strategy and policy-making decisions to control, monitor and protect the innovative electrical network.

Keywords: Control design, digitisation, distributed energy generation, distributed energy system, energy storage system, optimal control, renewable energy system, smart grids, state estimation.

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Contents

Abbreviations

AC	Alternating Current
AI	Artificial Intelligence
ANN	Artificial Neural Network
BESS	Battery Energy Storage System
DC	Direct Current

DEG	Distributed Energy Generation
DER	Distributed Energy Resources
DES	Distributed Energy Storage
DG	Distributed Generation
DMS	Demand Management System
EMS	Energy Management System
ESS	Energy Storage System
EV	Electric Vehicle
IoT	Internet of Things
LST	Least Square Technique
MAS	Multi-Agent System
ML	Machine Learning
MPC	Model Predictive Control
NN	Neural Network
PCC	Point of Common Coupling
PI	Proportional Integral
PID	Proportional Integral Derivative
RER	Renewable Energy Resource
SOC	State of Charge
VRE	Variable Renewable Energy

1. INTRODUCTION

Microgrids are the future perspective of the power grid by integrating distributed energy resources (DERs). These DERs are based on various distributed energy storage (DES) and distributed energy generation (DEG). This future perspective possesses different control and estimation techniques to secure the efficiency of the system operation, which can be tied to the power network or worked as a stand-alone. The accessibility of microgrid development permits the implementation of DERs in different current modes, such as direct current (DC) and/or alternating current (AC) [1]. The power electronic converters connect several DERs. This interconnection varies in terms of the function of the control loop characteristic, number and topology of the interconnected converters. Therefore, the dynamic performance of microgrids control loops can be affected due to converter interactions [2].

The microgrid encounters diverse challenges in meeting the system operation requirement and secure power-sharing. In grid-connected mode, for example, it is necessary at each sampling time to optimally coordinate power-sharing that ensure the reliability and resilience of a microgrid [3, 4]. The most challenging problems are the management of several microgrids with a high diversity of DERs [5], the control and protection system robustness [6], the uncertainty of supply from DERs due to the variable nature of renewable energy [7], and the uncertainty of demand sizing and location of the energy storage system [6, 8]. These challenges need a real-time demand management system (DMS) and energy management system (EMS) coordination within diverse DERs, and stability analysis modelling for different loading conditions [9]. Smart grid technologies apply innovative methods to solve these challenges. The technology and application of demand-side management based on flexible operations provide an excellent performance index and assist in reducing peak power, saving energy, minimising operation costs, and reducing greenhouse gas emissions [10]. The essential DMS are load shifting, flexible load shape, peak clipping, strategy conservation, and strategy load growth [9]. The demand response scheme is one of the smart grid applications for modelling various DMS [11].

The microgrid-based current flow control techniques and grid-connected inverter with DERs developed in [12] analyse various linear and nonlinear controllers. The assessment of existing control structures can mitigate grid synchronisation and power quality issues within a microgrid. In [13], a hierarchical control level is detailed for a DC microgrid to regulate and restore voltage and current and manage the power for primary, secondary and tertiary control layers. Rajesh et al. in [14] have reviewed different control techniques of AC microgrids in three aspects: active/reactive power, voltage and frequency, and droop controls within the hierarchical control architecture of microgrids. These three control techniques are also used to design the system controller of microgrids, and they can be considered approaches to design the control schemes, as detailed in [13] for droop control. In [15], four control techniques, namely proportional integral derivative (PID), robust, predictive and fuzzy, are assessed for distributed power generation. For instance, the PID controller is considered an approach in [12], and the fuzzy logic controller is also viewed as a control strategy in [16]. Therefore, this analysis aims to assess different control techniques that can be used for all types of microgrids. The control techniques developed in various research works for intelligent microgrid implementation are usually based on control strategies. Besides, a microgrid controller requires accurate data for a better performance index to ensure the efficiency of the power network. A microgrid is subjected to various anomalies and blackouts caused by equipment degradation, cyber security attacks and stochastic generation. Thus, these issues require effectively learning and monitoring DEG, DES and load flexibility, classifying and detecting various threats, and controlling multiple energy resources to mitigate threats and protect microgrid equipment [17].

This research identifies and classifies six control techniques as the principal conceptual development framework of control modelling for innovative microgrid applications. These are linear, non-linear, robust, predictive, intelligent and adaptive control techniques. The architectural selection of a given control technique considers the ability of the formulation to handle the control strategies of microgrids. The estimation techniques of the microgrid variables and parameters deal with the measurement and monitoring system to accurately reinforce the dynamic performance of control techniques [1]. The design and modelling of estimation techniques in the microgrids improve the dynamic behaviour of the system operation [18]. The intelligent microgrid performance constitutes various variables and parameters subjected to change in different exposures, such as energy resources, line parameters, faults, internal and external disturbances, variable demands, power quality, inaccurate data and cyber-attacks, etc. Thus, an assessment of essential estimation techniques is conducted in an intelligent microgrid that supports the control techniques. This work also provides a perspective vision for hierarchical and architectural control and estimation techniques for the effective operation of microgrids. These techniques optimally coordinate the components of microgrids from energy resources to the end-users, regardless of their current (AC and/or DC) and system structure.

The keys contributions of this work can be listed as follows:

- Assessment of the principal dynamic components for an effective operation of microgrid development and implementation in the innovative grid environment regardless of the types of current flowing. These depend on system control and monitoring to effectively manage microgrids and develop autonomous power networks.
- Analysis of the principal control techniques to be implemented in smart grids that can handle different control conditions based on system variables and the power quality of the microgrids. Therefore, the intrinsic system modelling and design of optimal control are addressed.
- The accuracy of the control schemes on the microgrid is an essential aspect to consider for system efficiency. Therefore, various estimation techniques that support the robustness and trustworthiness of the dynamic control scheme for smart microgrids operation are investigated.
- The perspective implementation for the optimal operation of intelligent microgrids to combine the control and estimation techniques is addressed. This effectively solves various challenges, establishes the future vision of microgrid development, and provides a framework for a digital thread that can assist in effective control and estimation techniques and digital twin modelling of microgrids.

2. SMART MICROGRID PERSPECTIVES

The smart grids deploy various sets of services and technologies to modernise the traditional power grid. This leads to an innovative power system that is automated, controlled, cooperative, secure and sustainable [19]. The microgrid is a suitable operating current system with the possibility to combine AC and DC power networks. Microgrid connects various DERs at point common coupling (PCC). A generic classification methodology is needed to detail the microgrid architectures, techniques, and challenges to understand the operation scheme. The architectures of microgrids contain off-grid [20] and grid-connected operating modes [21], while the accurate operation of the microgrid requires coordination of the EMS, load management system and control systems [22]. Therefore, the significant operation challenges of microgrids are optimisation, reliability, resilience, robustness and stability of the system [9]. These problems require real-time estimation based on measurement and monitoring of the network to track the system variables and parameters, which can accurately support the control schemes for the sustainable operation of microgrids.

2.1. Distributed Energy Resources

DEG and DES are the most popular types of energy resource used in microgrid operation, excluding the power generation from the the utility network [22, 23]. Besides, the DES is the new trend of the power grid that assists with the optimal supply of extra generated power within the network [24]. DEG contains renewable energy resources (RERs) and non-RERs, while DES includes a battery energy storage system (BESS) and non-BESS. BESSs are usually based on electrochemical technology, while non-BESSs use other types of ESS technology, such as chemical, thermal, mechanical and electrical technologies [25, 26]. This difference between BESS and no-BESS only emphasises a chasm with conventional battery based-electrochemical technology and other technologies-based-ESS. In specific scenarios, the energy demand is also considered part of

DERs because some loads are dynamic and offer a bidirectional power flow in the electric network [3]. RERs or variable renewable energies (VREs), such as wind power and solar photovoltaic, are the most popular source of DEG-based-RERs used in microgrids. The uncertainty of VRE resources and the need to satisfy the total power demand every hour make BESS technologies the essential improvement complement of the power grid in terms of flexibility, stability and reliability [27]. Besides, an electric vehicle (EV) possesses a mobile ESS technology that has been used in many applications of DER implementation for efficiently operating the electric grid [28].

2.2. Microgrids

Microgrid refers to the electrical network with a total or partial DER integration [29]. Table 1 describes the objectives of microgrid implementation in different modes compared to the primary grid [3]. The relationship between suppliers and consumers is a critical aspect of electrical network development. Regardless of the energy security and equity that aim to support the power grid efficiency, the equilibrium of resilience and reliability is the principal factor in sustaining the optimal operation of any given electrical network. [30]. Through the edge of DERs, microgrids increase the resilience and reliability of the power network to satisfy various stakeholders, such as distribution network operators [3], as summarised in Table 1.

Table 1: Microgrid objectives: Consumer and supplier relationship

Various Operating Modes of Future Power Grid	Reliability	Resilience
Only Main Grid: Consumer/Supplier [31]	✓	✗
Only Main Grid: Consumer/Supplier [32]	✗	✓
off-grid Microgrid: Consumer /Supplier [33]	✓	✓
Grid-tied Microgrid: Consumer/Supplier [34]	✓	✓

Resilience deals with stress events where the power grid can adequately adapt to the strain. The reliability of the system looks to handle the grid recovery taking into account the system compromise [35]. Thus, microgrids offer a customer engagement opportunity where the system reliability leads to sufficient flexibility between transportation and distribution of the energy [36]. Table 1 presents an exciting correlation between energy generation and consumption. An excellent relationship between the energy supply and demand eliminates unnecessary stress in the transportation system. In [37], several techniques and models to monitor the power grid reliability are presented. These are based on the most relevant emerging technologies with stochastic process and frequency strategies. Power grid reliability needs to be maintained during some operation conditions, such as hydrologic drought and heat wave conditions [38], and faults in the system [39]. In contrast, reliability makes the power grid sustainable against extreme events, including weather [40], climate change [41], and cyber security [42]. The grid-tied microgrid efficiently increases the reliability and resilience of the power network [43]. Through the DERs integration, an excellent relation between the end user, generation, distribution, and transmission of the energy can be provided [44].

The microgrid offers an energy flexibility strategy in residential, commercial and industrial sectors of power demand to tackle the different grid services. In the residential sector, this entails the triple core of building energy flexibility, including meeting the building needs of occupants and adapting to ambient conditions and flexible operations. DMS approaches are utilised to design energy-efficient and grid-interactive systems for energy flexibility [10]. These schemes are applied to all consumers for the proper operation of microgrids. In addition, various EMS schemes can resolve the real-time monitoring and coordination problem of a microgrid. The EMS strategies deploy microgrids in different power sizing, structures, and types [9]. Fig. 1 summarises prominent features, involving benefits and advantages, that support the implementation of microgrids and the common disadvantages of their development and deployment. Thus, microgrids can significantly improve the utility network [45] and provide a permanent power supply in developing countries [46].

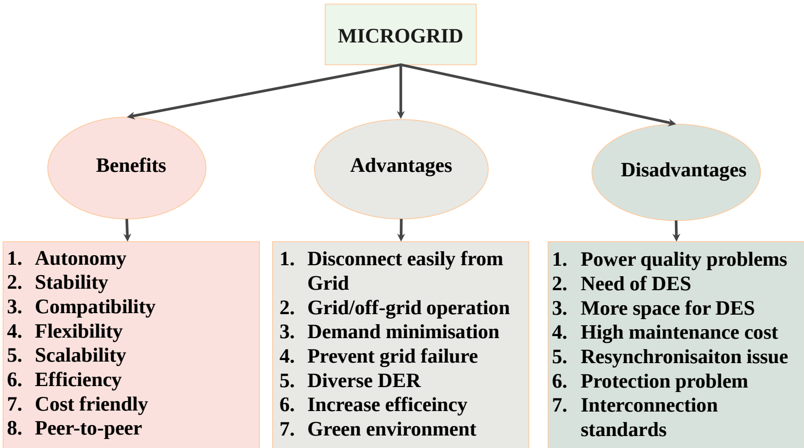

Figure 1: Microgrid: Benefits and the pros and cons.

2.3. *Smart Grid Technologies Perspective*

Modernising the conventional power grid improves the electrical network's connectivity, efficiency, security, and sustainability [47]. Intelligent technologies digitise the power grid environment and transform the polluted city into a green garden [48]. The transition from a conventional power network to a smart power grid environment is economically costly. It is also socially challenged by the traditional power system that people are accustomed to, especially in the old cities. However, several advantages in terms of system improvements in different aspects of operating microgrids are guaranteed. In [11], a comparative analysis between the traditional power grid and an intelligent electrical network is presented. The implementation of innovative grid technologies is complex and requires several steps to develop a smart power grid environment.

The microgrid is the novel architectural aspect of a power system that effectively implements all possible innovative grid technologies [49, 50]. The advantage of using the smart grid technology is to increase the power flow efficiency and reduce carbon emissions [51]. The innovative electrical power grid comes with different applications and technologies to solve most of the disadvantages of microgrids, as detailed in Fig. 1. The innovative grid technologies perspective constitutes various modelling methods and implementation approaches to optimally control and estimate the dynamic performance of microgrids. The concept of using innovative grid technologies to improve microgrid performance is presented in Fig. 2. The vision of this perspective is to reach Phase 5 (autonomous) operation of the microgrid. The microgrid currently operates in Phases between 2 and 3 (response-predictive). Phase 1-2 were the past of the electrical system, and Phase 4-5 will be, respectively, the near future and future of the smart grid. In Phase 4, which is the near future, artificial intelligence (AI) efficiently coordinates the dynamic relations of power system components, including power generation and transmission, BESS, DMS, EMS, EV integration and various DEGs. Phase 5 is the progressive vision of the previous one, with fully autonomous operations at all levels of the system components.

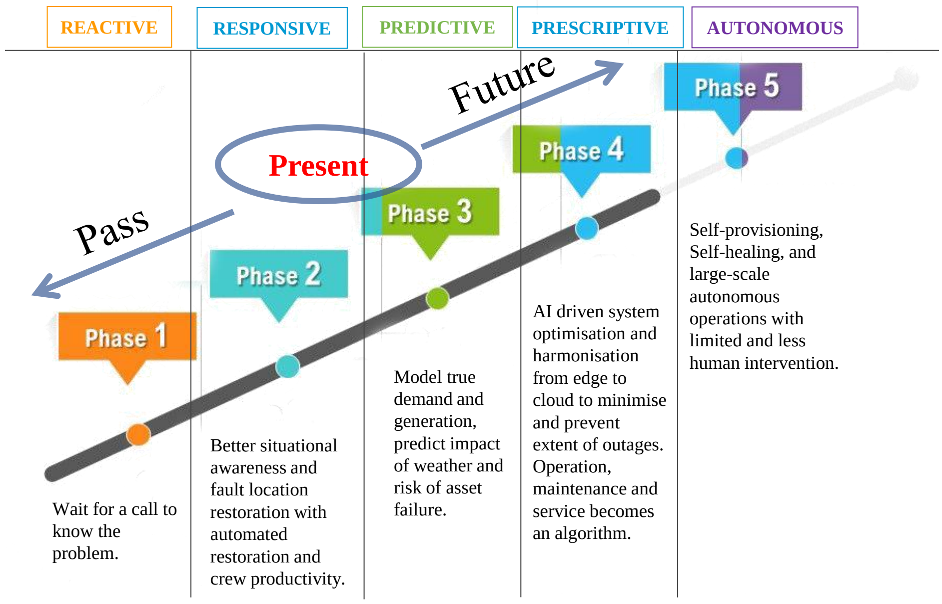

Figure 2: Journey to digital transformation in smart grids, adapted from [52].

3. CONTROL MODELLING AND DESIGN OF MICROGRIDS

Dynamic microgrid modelling depends on control, state and manipulated variables with all system disturbances. Therefore, the design of the control strategy should handle all variables and system disturbances subjected to specific constraints. Microgrid operation responds to three control layers to coordinate the system variables and guarantee the efficiency of the operation process. These are primary, secondary and tertiary control layers to handle the architectural control aspects of microgrids detailed in [13, 14]. A discussion of the control techniques of microgrids, especially in the intelligent grid environment, can be a little confusing to the scientific and technological communities [53, 54]. However, some approaches, such as active and reactive power, frequency and voltage, and droop controls [14], are essential to developing a design system for applying the control techniques. Figure 3 presents the control design block diagram for microgrid applications where distributed generators (DGs) significantly personify the control modelling. This shows that the most relevant control modelling and design strategies are combined with any estimation approach. The effectiveness of this control design in microgrids depends on the Phases of digital transformation, as presented in Fig. 2. The open-loop is simply a model without feedback on the manipulated variables, while the closed-loop model contains a feedback signal. The objects of the feedback of the closed-loop model are to stabilise the design model, compensate for the uncertainty of the design, reject the output disturbance, and attenuate the noise from the measurement for an accurate feedback signal [55].

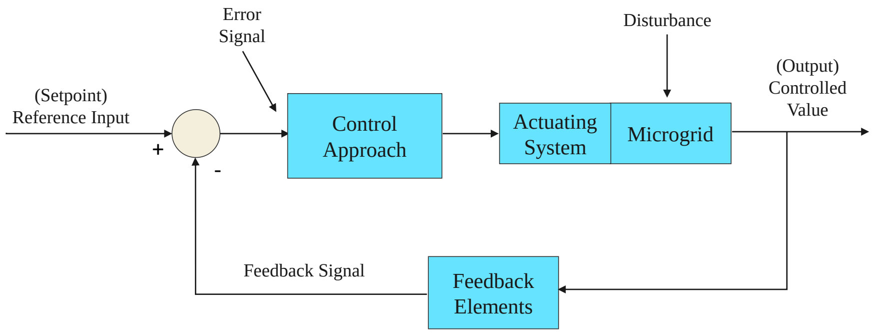

Figure 3: block diagram of control system implementation of microgrids.

3.1. System Model

A control system model for microgrid applications can be developed, as presented in Table 2. Thus, in Eq. 1 $\forall t \in N$ with t is the computation process sampling time, A, B, C, $x(t)$ and D represent the state matrix, the input matrix, the output matrix, the state vector and the disturbance matrix; and, $u(t)$ and $y(t)$ denote the control and manipulated variables [56]. In Eqs. 2-2, $G(s)$ represents the system transfer function, and it is expressed as $G(s) = y(s)/x(s)$ [57]; and, $h(t)$ denotes the impulse response of control system when the impulse signal is considered to validate a given design model [58]. A generic model of relevant linear control theories is presented in Eqs.1-3. Besides, two popular design schemes serve to model these types of canonical representation, namely deterministic and stochastic modelling, respectively, in Eqs. 4 and 5. In Eq. 5, $B_v(t)$ is a scaling and mixing matrix for the process noise input; I_v is an identity matrix depending on system design; $v(t)$ is vector/matrix noise which is defined by $v(t) = [v_1(t), v_2(t)]$, with $v_1(t)$ presents the process noise attached to $u(t)$, and $v_2(t)$ is the measurement noise attached to $y(t)$ [59]. It should also be necessary to notice that matrix D can also be considered in some design scenarios of Eq. 5. Thus, the deterministic formulation is a classical model of a state-space model without considering any uncertainty, as presented in Eq. 4 [59, 60]. However, the stochastic formulation has system uncertainty that contains probabilistic properties [59, 61].

Table 2: Control Techniques: Design modelling

Type	Domain	Canonical Representation	Eq.#
State-space	Time	$\begin{bmatrix} x(t+1) \\ y(t) \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} x(t) \\ u(t) \end{bmatrix}$	(1)
Transfer function	Frequency	$G(s) = C(SI - A)^{-1}B + D$	(2)
Impulse Response	Time	$y(t) = \int_0^t h(t-\tau)u(t)dt$	(3)
Deterministic modelling	Time	$\begin{bmatrix} x(t+1) \\ y(t) \end{bmatrix} = \begin{bmatrix} A & B \\ C & 0 \end{bmatrix} \begin{bmatrix} x(t) \\ u(t) \end{bmatrix}$	(4)
Stochastic modelling	Time	$\begin{bmatrix} x(t+1) \\ y(t) \end{bmatrix} = \begin{bmatrix} A(t) & B(t) & B_v(t) \\ C(t) & 0 & I_v \end{bmatrix} \begin{bmatrix} x(t) \\ u(t) \\ v(t) \end{bmatrix}$	(5)

Figure 4 presents a benchmark of dynamic system development and implementation for the overall control development in the intelligent microgrid. This representation is an advantage structuring that serves to classify and design the system approach, as presented in Fig. 3. The intrinsic control performance of an intelligent microgrid constitutes four interdependent systems: control techniques, control layers, control structures, and control strategies. The control techniques targeted in this research can be implemented and developed in any layer, design and method regardless of microgrid types and operational organisation. Furthermore, the control system guarantees voltage and frequency restoration, power balance, safe supply to non-linear loads, seamless transition, automatic islanding, and secure critical loads [9].

3.2. System Design

As presented in Table 2 of a given control system, the design modelling, including approach, layer, structure and technique, as illustrated in Fig. 4, can be either open-loop or closed-loop [62]. It should also be essential to note that some of the listed strategies can exclusively be implemented in closed-loop mode. The most popular types of design modelling used are based on Eqs. 1 and 2, respectively, state-space and transfer function models. The microgrid control modelling is designed in different layers and structures, as presented in Fig. 4. Table 3 describes various control layers of microgrid and their design formulation, complexity level and design domain. The control layers of the microgrid present the hierarchy control modelling and design. All the relevant optimal control schemes applied in the microgrid are developed based on the design domain of the control layer. Figure 3 details the control implementation for microgrid development. Microgrids architecturally and physically contain several DERs. Therefore, the formulation of the design model, as illustrated in Table 3, refers to the interconnection and interaction of several DERs for an efficient microgrid operation. For example, a given DEG placed at *ith* position interacts with all *j* DERs, as presented in the distributed control in Fig. 5.

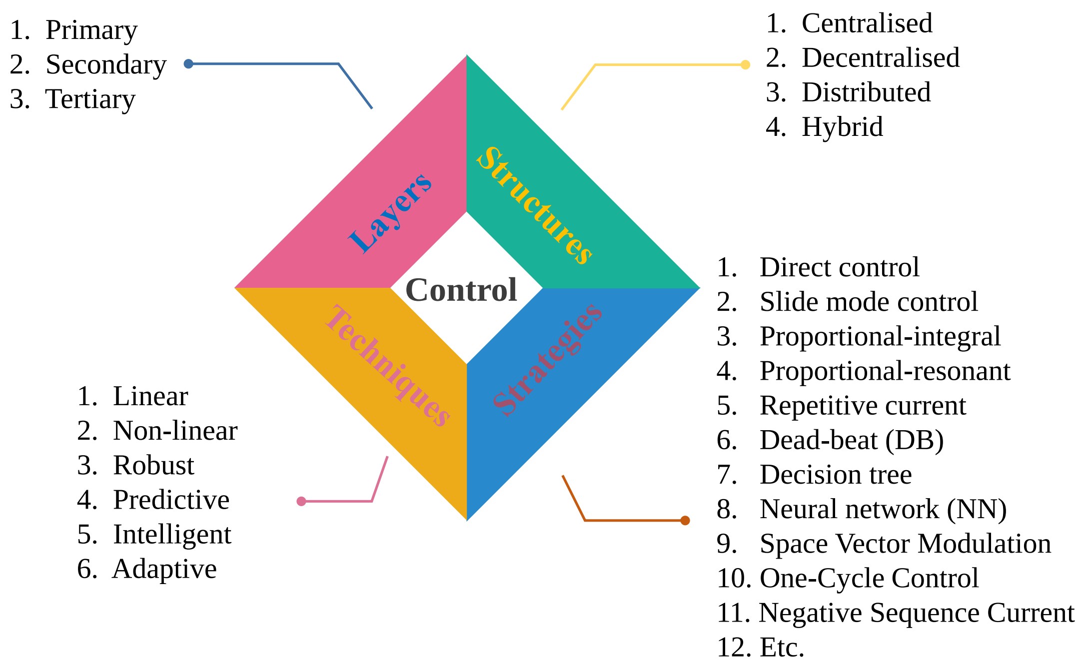

Figure 4: Vision of smart microgrid control development and implementation.

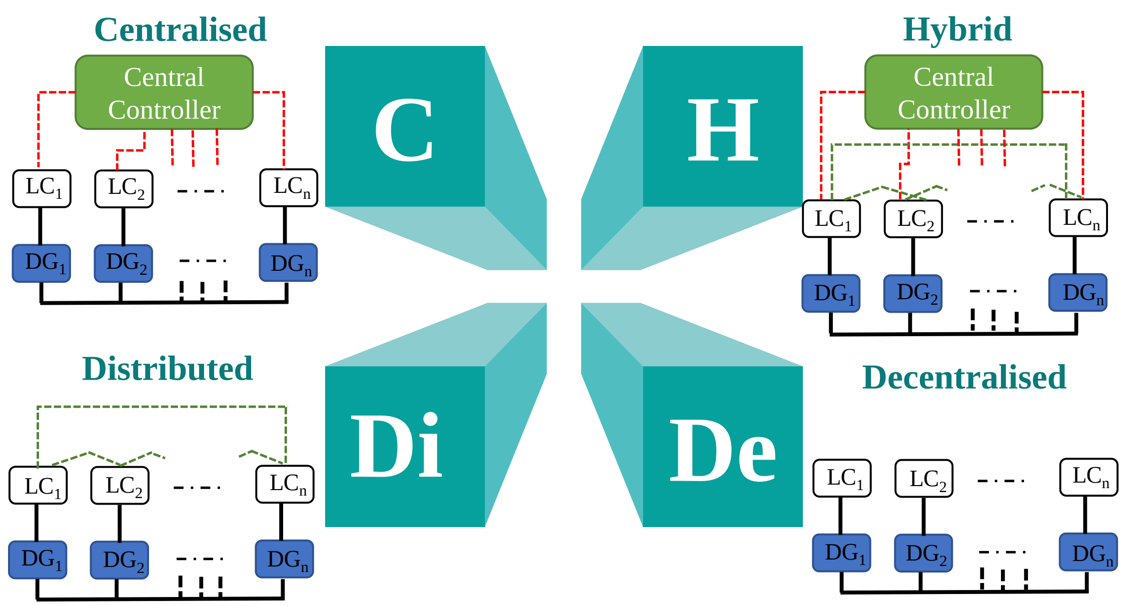

Figure 5: Control structure development in the electrical network.

Table 3: Microgrids: Control hierarchical framework

Layer	Design Domain	Design Formulation: Model	Eq. #	Time	Complexity level	Ref.
Tertiary	Economic Dispatch	$f(C_i(P_i), \alpha_i, \beta_i, \gamma_i, P_i, P_L, \lambda_i)$	(6)	$\geq$ 20 s	High	[63]
	Energy Management	$\underset{u}{min} \sum_{t=1}^{k} F\ (x_i(t), u_i(t), d_i(t), z_i(t))$	(7)	$\geq$ 20 s	High	[64]
	Congestion Management	$minf = (pr, \Delta S_{G_i}, P_{ll_i}, \Delta S_{L_i}, \Delta S_{L_s}, t)$	(8)	$\geq$ 20 s	High	[65, 66]
Secondary	Frequency Restoration (AC)	$\begin{cases} \omega_i = \omega^* - m_i P_i + \Omega_i \\ k_i^{\omega} \frac{\mathrm{d}\Omega_i}{\mathrm{d}t} = (\omega^* - \omega_i) - a_{ij}(\Omega_i - \Omega_j) \end{cases}$	(9)	2 to 10 s	Moderate	[67, 68]
	Voltage Restoration	$\begin{cases} E_i^{ref} = E^* - n_i Q_i + \partial E_i \\ k_i^{E} \frac{\mathrm{d}(\partial E_i)}{\mathrm{d}t} = \beta_i(E^* - E_i) - a_{ij}(\frac{Q_i}{Q_i^*} - \frac{Q_j}{Q_j^*}) \end{cases}$	(10)	2 to 10 s	Moderate	[69, 70]
	Power-Sharing Improvement	$\begin{cases} P_i(\text{active power}) = f(\text{Eq. } 9) \\ Q_i(\text{reactive power}) = f(\text{Eq. } 10) \end{cases}$	(11)	2 to 10 s	Moderate	[71]
Primary	Frequency Stability (AC)	$f(E_k, J, J_{vi}, \omega_e^*, \omega_i, \dot{\theta}_{si}, \dot{\omega}_{si}, D_{pi}, P_i^*, P_i, p_i, t)$	(12)	0.2 to 1 s	Low	[72, 73]
	Voltage Stability	$f(\delta E_i^1, k_{pE}, k_{iE}, E^*, E_{id}, \bar{e}_i, \bar{e}_j, t)$	(13)	0.2 to 1 s	Low	[74]
	Power-Sharing	$f(u_{Qi}, C_{Qi}, \delta\omega_i, C_{Pi}, a_{ij}, \frac{Q_i}{Q_i^*}, \frac{Q_j}{Q_j^*}, \frac{P_i}{P_i^*}, \frac{P_j}{P_j^*})$	(14)	0.2 to 1 s	Low	[75]
	Power Quality	$f(\text{Eqs. } 12\text{-}14)$	(15)	0.2 to 1 s	Low	[76, 77]

The tertiary layer is formulated in Eqs. 6-8. In Eq. 6, $C_i(P_i)$ presents the operational cost associated with a given *ith* DEG unit. Thus, the cost function coefficients are presented by α_i, β_i, and γ_i, with α_i and β_i are the quadratic cost functions values associated with the generation i; λ_i represents the estimation of the incremental cost for each generation; P_i and P_L are respectively active power from DEG i and power demand of the system. In Eq. 7, $x_i(t)$ represents the discrete time-dependent variables, including the energy cost [78] and the battery state of charge (SOC) [64]; $u_i(t)$ denotes the control variables; $d_i(t)$ is the parameter vector including fuel cost, intermittent generation, the best available estimation of demand at a given time, etc.; z_I represents time-independent variables, including frequency, phase angles and voltages. In Eq. 8, pr denotes the dynamic electricity price, depending market, bid prices for each generation and each load demand; $\Delta S_{G_i} = \Delta P_{G_i} + j\Delta Q_{G_i}$ is the power from the generator i which is a function of up and down generation shifts, $\Delta S_{L_i} = \Delta P_{L_i} + j\Delta Q_{L_i}$ is the energy demand for given load i which is the function of up and down generation shifts; P_{ll_l} is the lost load value; and S_{L_s} is the amount of involuntary load shedding.

Hou et al. [79] have proposed a multi-objective scheme to coordinate the economic dispatch of microgrids with EV and transferable load. The advantage of the economic dispatching design domain is that it can be formulated in different structures, as presented in Fig. 5, and handle communication delays [80]. The energy management design domain is one of the most popular schemes formulated in several tertiary control layers of different microgrids. For instance, in [81], an optimal combinatorial control scheme based on an energy management scheme is formulated to model the economic dispatch of a standalone microgrid to maximise the use of ESS. In [82], a decentralised structure is developed using energy management to optimise the charging process of EVs for off-grid microgrids. Futhermore, the energy market has become a multiplex environment where several stakeholders play a significant role [83]. Congestion management creates a hosting domain where all actors, such as transmission system operators [84], distribution system operators [85], end-users, etc., equitably accommodate the energy market that considers an extensive integration of DERs [86].

The secondary layer is formulated in Eqs. 9-11. In Eq. 9, ω, Ω, m, $k_i^\omega > 0$ and P denote frequency, frequency restoration variable, droop coefficient, velocity regulation coefficient of secondary control and active power. All variables and/or parameters can be attached to DEG i; a_{ij} represents the adjacency matrix elements for assessing the communication architecture where its weights coefficients, a_{ij}, can be exploited to evaluate the microgrid stability, and node j denotes communicated agent in relation with node i [87]. In Eq. 10, E, ∂E_i, n and Q_i/Q_i^* indicate the regulating voltage, secondary control variable, droop coefficient and normalised reactive power of the DEG$_i$. β_i and k_i^E are positive gains that are used to modify the dynamics. Ref. [88] presents a distributed hierarchical control approach based on three-layered architecture and droop control for islanded microgrids. This model aims to solve the single-point failure of a centralised control structure. The secondary control serves to balance the power-sharing between microgrids [89]. In the secondary control layer, a better design of one domain can also solve the problems of other domains. For instance, A distributed control in the second layer covers both frequency and voltage restorations of AC microgrids [90]. In [91], a robust frequency restoration that ensures the active power sharing of isolated microgrids is presented.

From Eqs. 12-15, the primary control layer aims to regulate the microgrid operation, which consists of developing active power, frequency, reactive power and voltage regulators to stabilise microgrids and guarantee the quality of the power flowing [92, 93]. Most of the variables/parameters in this layer are identical and can also be identified in the second layer. For example, in Eq. 12, E_k is the kinetic energy, J_{vi} is the virtual inertia, ω_e^* is the nominal frequency, ω is the rotational speed, J is the rotational inertia of the synchronous generator, and D_{pi} is the virtual friction coefficient. From Eq. 13-14, δE_i^1 is the voltage compensation generated by E^*, which is the reference voltage that is compared to the observer output; $\bar{e}_i$ represents the voltage-observer output; $\delta\gamma$ defines the transient deviation generated by the consensus of the active power; C_{Qi} and C_{Pi} are the coupling gain. k_{pE} and k_{iE} denote the control gain for proportional-integral (PI) control. It is necessary to note that these gains depend on the control strategy used to formulate the design model. u_{Qi} voltage of DEG i to regulate reactive power, and P_i/P_i^* illustrates the normalised power of the ith DEG.

Microgrid stability is an essential aspect to consider for optimal operation [94]. This is because microgrids constitute of interconnected system where dynamic stability is the first requirement to guarantee the dynamic stability of DEG. The inertia control is one of the promising schemes to guarantee the frequency stability of microgrids [95]. An effective primary layer control leads to excellent power-sharing and voltage stability in DC [96] microgrids, while in AC microgrids, frequency stability is also added [73]. The primary layer is the foundation of the system operation of microgrids [97]. The hierarchical control scheme combines two or more layers, as presented in Table 3. This type of control design enhances the performance of microgrids concerning power quality, regulation, stability, and coordination. In [98], architectural control based-two layers, primary and secondary, is suggested to minimise the power oscillations of diverse DGs for microgrids. The first layer develops a dual current controller to generate the current reference and suppress the active power oscillations. Additionally, the secondary layer is formulated through an optimal model to simultaneously minimise the oscillating amplitudes of both reactive and active powers. Therefore, in most scenarios, a successful control design of microgrids is based on hierarchical control architecture.

4. CONTROL TECHNIQUES

All control techniques of a microgrid are developed following the hierarchical design formulation presented in Table 3. The current control design of the microgrid aims to move the predictive power network to a prescriptive electrical grid to meet the future vision of the autonomous power grid, Phase 5, as presented in Fig. 2. Figure 4 illustrates the most relevant control techniques identified for microgrid applications. The advantages of this type of classification of control techniques are that all the design approaches can be developed in any style depending on microgrid modelling and improvement requirements using design modelling development, as shown in Table 2. Furthermore, this can be based on any stochastic or deterministic modelling to handle the dynamic performance of the optimal control strategy..

4.1. Linear Control Techniques

Consider the formulation of the control models, as presented in Table 2, the linear model can be formulated as linear time-invariant as follows [78]:

$$\begin{cases} \dot{x} = f(x, u, t) \\ y = h(x, u, t) \end{cases} \tag{16}$$

Eq. 16 is a functional representation of state-space modelling represented in Eq. 1. Linear control technique based on the closed-loop design can have the form of Fig. 3. This technique is simple to implement and possesses a fast response. The method can assist in regulating the frequency and controlling the current of a microgrid [16]. Eq. 2 is also used to design a linear control mode. In [99], a load frequency control of a microgrid based on a transfer function modelling is implemented to smoothly switch the energy management of DEGs.

Several control approaches, such as PI [16], proportional derivative, proportional-resonant and repetitive current controllers, can be implemented based on linear control techniques [12]. Figure 6 describes a PID control approach, which can be efficiently developed using this method. The linear control technique can be designed within the primary and secondary control layer of a microgrid to create respectively current and voltage control loops [53]. For a given time t, the control signal, u, fed the operation to be controlled, as presented in Fig. 6; therefore, the linear formulation of classical a PID scheme can be reformulated as [100]:

$$u(t) = k_p e(t) + k_d \frac{de(t)}{dt} + k_i \int_0^t e(\tau) d\tau \tag{17}$$

where k_p, k_d and k_i are respectively proportional, derivative and integral gains; $e(t)$ represents the error of signal, which is a function of the difference of desired/set point and measured operational output, respectively r and y. In the discrete mode for computational implementation, Eq. 17 with a sampling time k can be formulated as $u_{PID}[k] - u_{PID}[k-1] = k_d \Delta^2 e[k] + k_p \Delta e[k] + k_i e[k]$ with $\Delta^2 e[k] = \Delta e[k] - \Delta e[k-1]$ and $\Delta e[k] = e[k] - e[k-1]$ [101].

The linear dynamics containing small-signal modelling have an essential drawback that cannot face large-signal disturbances for an efficient microgrid operation [102]. Nevertheless, the linear control techniques can also be developed into a tertiary control layer to solve energy coordination problems. In [103], a linear control technique based on a demand response scheme to compute open and closed-loop models is presented. Quadratic issues of DER power-sharing, such as ESSs, can also be resolved using linear quadratic modelling [104]. A linear quadratic Gaussian problem under a centralised control structure to optimally manage the intelligent network microgrid is developed in [105]. This is performed under secondary control levels with various independent agents within the system. Finally, in [18], a primary control-based decentralised structure using linear quadratic Gaussian for off-grid and grid-connected operating modes of a microgrid is devised.

Xu et al. [106] assess some particular linear techniques, such as feedback linearization and Takagi-Sugeno fuzzy, to coordinate bidirectional DC-DC converters of microgrids. The specificity of these methods is their ability to transform a non-linear system into a controllable linear system. In [107], a linear droop control based-combining sliding mode and Takagi-Sugeno fuzzy to remove the non-linearity of the system for smart power-sharing of DC islanded microgrids is designed.

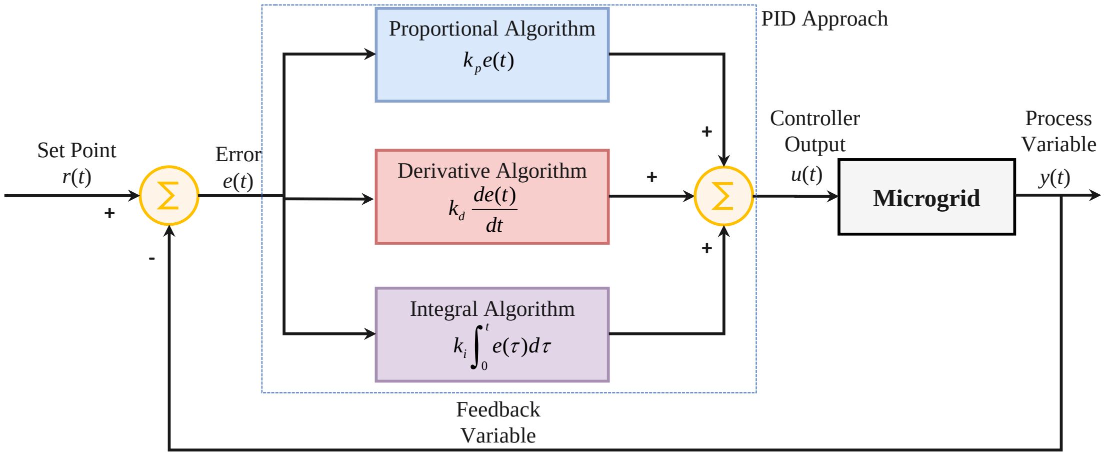

Figure 6: Block diagram of PID control approach.

4.2. Non-Linear Control Technique

The state model of non-linear control technique can have several forms depending on a given system model. Eq. 18 presents an example model of non-linear design.

$$\begin{cases} \dot{x}(t) = f(x(t)) + g(x(t))u(t) + w(t) \\ y(t) = x(t) \end{cases} \tag{18}$$

where $w(t)$ denote the bounded disturbance, $g(x(t))$ and $f(x(t))$ represent the non-linear functions that may need to be linearised for the optimum solutions of the control design. The non-linear control technique has the possibility to design various control schemes, such as PI, PID, dead-beat (DB) and hysteresis controllers [12]. PI, PID and fuzzy logic controls are the most suitable non-linear techniques to balance ESSs and stabilise the bus voltage of the DC microgrids. Besides, They can handle the restriction of current sharing and the harmonisation of power flow. These control schemes are developed at the primary control level [13]. A passivity-based control strategy is considered as one of the effective practical non-linear control for bidirectional DC-DC converters. Moreover, the approach is straightforward to implement [106].

A droop control can allow the self-healing of cluster microgrids. Through DER control based-non-linear primary control, the system voltage and frequency at PCC are stabilised, and the active and reactive power sharing between microgrids is achieved [108]. A mixed integer non-linear programming methodology to compute the droop control for an optimal operation of microgrids in off-grid and grid-tied modes is presented in [109]. This is a convex optimisation strategy based on optimal power flow using smart grid technology to effectively control the microgrids. The non-linear control technique accurately resolves the energy flow problems of microgrids compared to the linear method [110]. The slide mode control is an advanced non-linear control technique to apply. Furthermore, this approach offers a robust and straightforward configuration [106].

4.3. *Robust Control Technique*

The robust control technique uses various control strategies to support the interconnection control of DER units and guarantee suitable energy conversion. This control technique increasingly dwells on the loops of the microgrid inverter control. It is involved in voltage, and frequency controls under unbalanced conditions, often designed with the infinity horizon [15]. Direct control and slide mode control strategies of DGs for microgrids can be developed under the robust control technique [16, 111]. The direct power control coordinates the synchronisation of the microgrid [15, 111]. The robust control technique also operates under different loading conditions. In [53], an advanced exponential sliding mode control strategy based on the power-rate method is presented to coordinate multilevel/parallel inverters for microgrids operating under balanced and unbalanced loading conditions. This is a robust control technique that offers an accurate and fast performance regardless of system variations. Robust control modelling uses the same philosophy of stochastic formulation developed in Eq. 4. However, the robust formulation considers only the uncertainty of the system description, which does not have probabilistic properties. For instance, suppose at time t, an unknown disturbance vector $w(t)$ with a known parameters matrix B_d, thus, the robust modelling can be formulated as presented in Eq. 19. This formulation of robust control technique has proven its effectiveness on model predictive control (MPC) design strategy [59].

$$x(t+1) = Ax(t) + Bu(t) + B_d w(t) \tag{19}$$

The robustness of the controller for microgrids often combines several layers. Therefore, a hierarchical control for the seamless transition of microgrid operation modes is developed in [112]. A hierarchical control scheme solves the robust control problems for the efficient operation of microgrids [9]. The structure of the model, designed in [112], is generalised and does not require a forced switching between district controllers of inverter-interfaced DEG. A fixed voltage reference generation strategy is applied for a droop control method to accommodate microgrid operation modes. This is combined with an offset-free voltage control scheme to handle the modified voltage-current controller. A feedforward system is designed to estimate the inner current loop reference fluctuations and create a disturbance observer, enhancing the control dynamics for a suitable cascaded voltage-current approach. This is a robust control scheme without remote measurement and communication where the disturbance observer strategy combines disturbance compensation and general tracking. The system uses a proportional controller for fast dynamics in the inner loop. The robustness of the proposed model attenuates structure and external power disturbance effects and assists in the flexibility and smooth transition of a microgrid operation.

Xu et al. [27] propose a discrete robust control scheme to coordinate grid-tied inverters of BESS. The developed model fully balances the battery SOC to exploit the maximum capacity of the BESS and minimise the power-sharing with the primary grid. In addition, the disturbance estimation technique is added to handle system uncertainty and disturbance. Besides, a saturation function alleviates the chattering problem. Thus, the distributed control approach prioritises convergence and stability to guarantee the performance requirement. As a result, the fair energy exchange between supply and demand is observed within the microgrid.

4.4. Predictive Control Technique

The predictive control techniques forecast and predict the future dynamic behaviour of a given plant. Two methodologies are used to model predictive control techniques. The modelling methods for predictive control technique are neural networks and deterministic or statistical time series [16]. The most predominant predictive control scheme based on deterministic optimisation modelling is MPC. Figure 7 presents the optimisation strategy of MPC for optimal control of a microgrid. For the neural network modelling method, the artificial neural network (ANN) is formulated to adapt and calculate the system dynamics of the microgrids promptly. Besides, the MPC scheme can be designed in linear and quadratic models [3]. The control block diagram used the same conceptual framework presented in Fig. 6. Eq. 20 describes the quadratic MPC design performance index [22].

$$J(k) = \sum_{i=0}^{N} [x^T(k+i|k)Qx(k+i|k) + u^T(k+i|k)Ru(k+i|k)] \tag{20}$$

where $J(k)$ presents the objective function of predicted sequences, N is the control horizon, and Q and R are diagonal matrices with positive elements; these elements express substantial weighting matrices of the design model [62]. The MPC performance index can be subjected to various constraints, such as state variables, input variables and their increment signals, output variables, DEGs constraints, demand constraints, etc. The optimal solution of MPC, as presented in Fig. 7 with the objective function developed in Eq. 20, aims to compute the control variables as follows:

$$u^*(k) = \arg \min_u J(k) \tag{21}$$

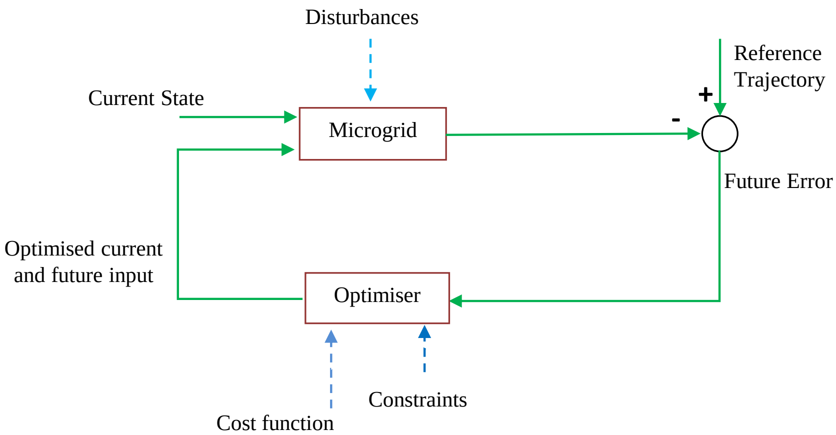

Figure 7: Optimisation block diagram of MPC, adapted from [21].

MPC is often developed at the tertiary control level. This strategy resolves energy conservation issues and actively maximises the DC microgrid operation [13]. Moreover, MPC is a robust control scheme that can optimally handle system disturbance and uncertainty [113]. Thus, the predictive control techniques based on the MPC and ANN, depending on the system achievement, can be effectively modelled for all three aspects of intelligent microgrids controller levels, from primary to tertiary, in DC and AC power systems. The dead-beat strategy can also be developed in the framework of predictive control techniques [114]. The decisive advantage of the predictive control technique leads to various implementation strategies in the framework of machine learning (ML) methods, such as NN, regression trees, linear regression and support vector machines, to approximate the MPC performance index for current control of cascaded H-bridge converter for innovative microgrid application [115].

4.5. *Intelligent Control Techniques*

Intelligent control techniques use software and hardware technologies to model the dynamic control performance of microgrids [116, 117]. The soft computing technique is also known as the intelligent control technique-based programming languages and/or data-driven models [118]. The data-driven strategy is one of the intelligent control techniques that offer several opportunities for both linear [119] and non-linear [120] models, as presented in Eqs. 16-18, with (or without) multiple control and state variables. The advantages of data-driven are the ability to generate a model from data, the aptitude for learning the control behaviour, and the placement of sensors and actuators for a system with several variables [55].

The intelligent control technique is scalable and robust for state estimation to permit accurate and continuous monitoring of power grid operation and user behaviour in a real-time environment for excellent dynamic control [19]. The softest computing approaches used to control intelligent microgrids are AI [121], ANN [122], deep learning [123], deep neural network [124], fuzzy logic control [125], fuzzy neural network [126], ML [127], particle swarm optimisation [128], wavelet transform [129], etc. Soft computing is mainly considered a platform with different intelligent tools that can improve the robustness and the function of control steps. Their applications are repeatedly seen in the context of active and reactive power and power electronics to sustain microgrid operations [16] and substantially decrease the computational complexity within the system performance index [115]. Additionally, fuzzy logic control, particle swarm optimisation and genetic algorithm can be designed within the tertiary control level to coordinate the energy flow of the DC microgrid [13].

The hardware technologies apply the innovation technologies-based-fast communication network to control the microgrids intelligently. The Internet of things (IoT) technology is one of the intelligent modelling visions to control microgrids smartly. This intelligent controlling innovation is from power resources to the end-users [48]. The energy internet, or the internet of energy, uses the innovation of connecting things, people, energy, services, etc., from the IoT to design the smart energy mix models that can solve the present energy challenges [130]. Two-way communication is the socket modelling for the intelligent control technique using hardware models. For example, Prabhakaram et al. [131] have modelled a control area network to enhance the drawback of load sharing from traditional droop control. The novel communication uses low bandwidth to accurately achieve load sharing with an excellent voltage regulation of a DC microgrid. Moreover, the model is stable enough to handle the impact of communication delays. This is devised through a distributed control structure.

4.6. Adaptive Control Technique

The adaptive control technique offers a broad range of methodologies containing different strategies applied to the previous control techniques. For example, in [132], an adaptive control technique is used to design a time-of-use MPC for an energy management system. In [133], a novel adaptive PI control for the microgrid is presented to stabilise both frequency and voltage in the presence of diverse variations of loading conditions regardless of their types. The adaptive control technique is also suitable for developing the intelligent microgrid controller in different layers, primary, secondary and tertiary, as presented in Table 3.

Power-sharing between DGs cannot be accurate when the feeder/line impedances are mismatched for islanded microgrids. The drawbacks of decentralised methods of active power in inverse droop control and reactive power in conventional droop control can cause this. One of the most popular techniques for resolving this challenge is virtual impedance which requires an adequate setting value. Therefore, an adaptive control methodology is developed to adjust the virtual impedance concerning the output current of DGs. This technique does not require additional communication equipment or sensors and network load/parameter estimations, but it improves the power-sharing performances of islanded microgrids [134].

Afshari et al. [102] develop novel cooperative fault-tolerant control protocols for AC microgrids under the secondary control layer. These protocols coordinate the adaptive fault-tolerant control of active power, frequency, SOC and voltage with their respective distributed observer to ensure synchronisation of the microgrid regardless of its topology and parameters. The scheme is developed under a distributed control structure to guarantee the control variable of each adaptive control technique. The distributed reference observer estimates the leader trajectories based on the neighbour information during the faulty condition. The algorithms regulate the frequency and voltage of independent microgrids under various defective conditions. The model also provides accurate power-sharing and achieves the SOC balance among the DESs.

Energy-sharing among DERs is essential to consider for a dynamic performance of a microgrid. A voltage drop compensator of a smart DC microgrid considering versatile scenarios is designed using a model reference adaptive control in [135]. The model realigns the energy reference to proportionally share the demand among multiple hybrid ESSs within a DC microgrid. it is observed that a decentralised control structure for ESSs provides steady-state and transient power response to the DC microgrid bus. The designed scheme is tested in small-signal stability and aimed to compensate for the deviations of power that dissimulate from line parameters.

5. ESTIMATION TECHNIQUES

The estimation techniques of the smart grid are well performed in most scenarios to cover several accurate gaps that the control techniques cannot handle. An excellent control strategy depends on the precise measurement of control and state variables to perform robust coordination of the system that can satisfy the desired value of the manipulated variables [113]. For instance, in [2], it is observed that the stability and performance of DC microgrids are mainly affected by the interactions of multiple loads and source converters, regardless of the individual control strategies of the converter. Thus, a loop gain strategy based on the DC bus online stability monitoring and damping the DC bus is presented. This approach controls the source converter voltage loop gain and estimates and monitors the peak value of the bus impedance. The accurate estimations of variables are required for suitable control methodologies and reliable microgrid operations [136].

As detailed in Fig. 4, the secondary control layer contains centralised, decentralised and distributive control structures that can efficiently implement the most relevant estimation techniques [13]. Fig. 8 depicts the most important variables to consider in developing the estimation techniques for efficient protection and operating systems of intelligent microgrids. Furthermore, the estimation of the parameters of microgrids can be regarded as an appraisal-based modelling technique. Therefore, the estimation techniques can be implemented throughout the microgrid hierarchical control schemes. Besides, some of the most effective methods of estimation techniques are not within the three hierarchical control levels of microgrids, as demonstrated in Table 3. These include DERs estimation and/or forecasting [137], and also microgrid equipment ageing [138] and their optimal sizing estimation [139].

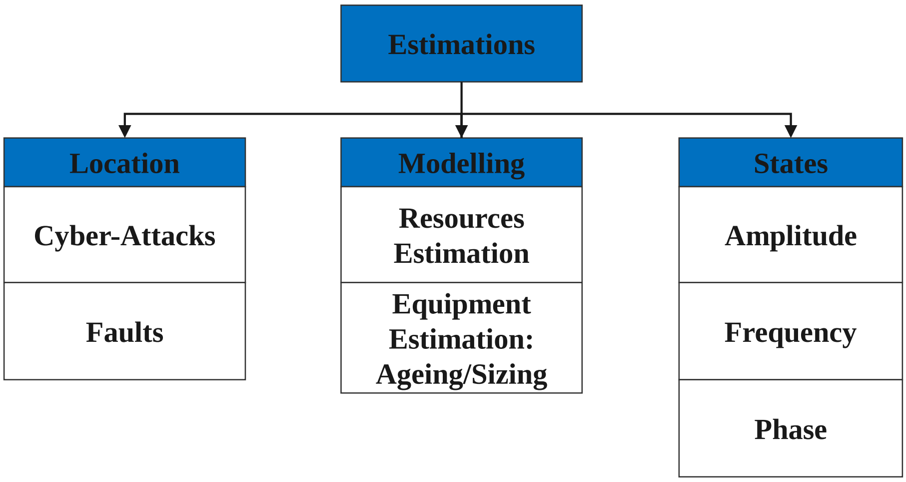

Figure 8: Summary of most relevant parameters/variables.

5.1. Kalman Filter Technique

The Kalman filter is one of the best techniques for state estimation during sensing scenarios for an intelligent microgrid. State estimation is crucial for accurate monitoring, and robust control of a given dynamic system [140]. Therefore, a state estimator program to communicate with the control centre that senses the system component to estimate the states of multiple DERs of the microgrid is presented in [19]. Power network applications, such as power quality supervision, condition monitoring, and protection, depend on the precise measurement of amplitude, frequency and phase of a sinusoid with various noises and harmonics. A novel adaptive robust Kalman filter to estimate the fundamental harmonic phasors and frequency is presented in [141] by using the H-infinity method. This powerful strategy is applied in intelligent microgrids with DEGs to detect non-islanding, islanding and switching events to tack and accurately approximate the time-varying power grid harmonics. The developed model is superior to traditional algorithms in accuracy and convergence speed.

In [18], a solution based on linear-quadratic to estimate and regulate the observer and feedback gain problems is designed. This is based on a stationary Kalman filter. The formulation strategy supports the optimisation trajectory of state variables to handle the desirable values of the primary control for a suitable AC microgrids dynamic response. The frequency and voltage amplitude considered for a robust decentralised control deal with the model uncertainties. In [47], optimal feedback control is developed to protect against cyber-attack and control the microgrid. A recursive organised convolution code and Kalman filter are formulated in a smart grid environment. The system states are impacted by cyber-attacks and random noises. Thus, the Kalman filter estimates the states, and the optimal feedback control regulates the microgrid states for an efficient operation. The proposed strategy accurately mitigates the microgrid cyber-attacks and efficiently evaluates and controls the microgrid states. Elnady et al. [111] combine super-twisting and Kalman filter techniques for state estimation for optimal slide mode and direct power controls. The combination technique performs an excellent seamless dynamic and steady-state operation of microgrids with minimum power chattering.

5.2. Estimation Techniques Base-modelling of Microgrid

The equivalent dynamic models for microgrids need more attention for large-scale electrical network topologies. Prony assessment is a function dependent on a sum of damped sinusoids. The non-linear least-square based-optimisation strategy is necessary as a parameter estimation technique to measure all function parameters. This strategy accurately determines the microgrid dynamic model by the use of data from phasor measurement units at the PCC. This is seen as a dynamic modelling estimation of an intelligent microgrid regardless of parameter disturbances [142].

In [143], an equivalent Thevenin circuit based on static and dynamic methods is modelled to estimate the interconnection of inverters for an islanded microgrid. First, the static impedance circuit is developed to assess the system, and then a dynamic second-order resistor–inductor branch is generated. The static circuit has an excellent steady state with an inadequate transient response, while the dynamic circuit covers the static circuit with acceptable short behaviour. Therefore, changing resistances and inductance in the equivalent impedance is reasonable for developing accurate estimating models.

In [144], frequency estimation of the microgrid to deal with power mismatch between the generation and consumption causes varying topology and frequent switching in an innovative grid environment. Thus, a subspace technique is developed to estimate the frequency in a real-time environment under an unbalanced and balanced power network. Widely linear modelling is applied to this technique, compared with the intricate least mean square technique and its augmented technique. It is perceived that the developed plans achieve remarkable precision and time. The grid impedance estimation method is a full-blown estimation technique widely developed in power systems. In this study, it is classified under the modelling of the microgrid estimation technique. In [145], an intelligent grid impedance estimation approach is designed to accurately and quickly estimate impedance under distorted and unbalanced network conditions. The method applies the intrinsic switching behaviour of a grid-integrated power converter to deal with the excitation of the grid response. This strategy no longer requires purposely injected disturbance signals. Therefore, the developed procedure is beneficial in several applications of the grid-integrated power converter, such as active filter control, islanding detection, impedance stability assessment, etc.

5.3. Data-Driven Techniques

AI and ML techniques enable detection algorithms that distinguish various scenarios in operating power grids by detecting active and passive devices. An estimation technique based on data mining is presented in [146]. Based on the frequency-domain analysis, the active device connected to the microgrid can be detected by rapid production and using specific harmonic profiles. The strategy aims to retrieve information that can also retrieve unexpected information to accurately predict the state of the microgrid and the energy needs on the consumer side. Moreover, this method does not require a dedicated communication channel, and it effectively manipulates the harmonic response of active devices.

The detection and isolation of arc faults in solar power devices, DC microgrids, are challenging to estimate. Therefore, a cross-correlation technique is applied to extract and distinguish the signal pulses. This strategy uses a planar location with two detection points to locate the DC arc faults. The estimation technique is based on a NN and received signal strength indicator to determine the distance of the arc. The strategy introduces within the algorithm a data-augmented NN approach. The method covers a significant location error due to insufficient data from the dual detection points to train the NN. Therefore, the estimation technique is accurate and robust for distance location and detecting faults in different arcing conditions. Due to the intrinsic immunity of the developed method to standard current fluctuations, this strategy can be effectively applied in another type of intelligent microgrid to detour inappropriate trips and enhance fault protection effectiveness [147].

The load demand depends on several factors, such as human behaviour, time, available power to be supplied, etc. In contrast, human behaviour is a function of various aspects, such as socioeconomic and environmental factors, depending on weather conditions. Therefore, a framework to estimate load power data in the position of human behaviour and period is presented in [148]. The strategy applied machine learning under the demand response scheme to predict the switching state on the demand side. It has been observed that the automatic controller function can increase the machine learning algorithms for accurately estimating the load demand data. The advantage of the machine learning application technique is that it offers several algorithms, such as NN, artificial intelligence, etc., to estimate the states, locations and model (sizing) of the specific variable, component and the entire microgrid.

5.4. Communication Technique

The communication network is essential in continuously monitoring power system parameters in the innovative grid environment. IoT technologies deploy different sensing patterns within the network to provide power components (DERs) interaction for better-estimating parameters. For an accurate estimation technique using IoT technologies, the number of sensors should be equivalent to the number of states estimated [19]. An online monitoring and tuning strategy are developed to dynamically stabilise a DC microgrid [149]. The model can be classified within the estimation technique based on communication, which differs from the method developed in [19, 150], where the communication techniques are specified. The online strategy applies a real-time environment that depends on communication from the supervisory controller. Through the voltage loop phase margin, the online method estimates the peak bus impedance, which is kept to its acceptable region by adeptly tuning the voltage regulator compensator gains. The proposed online approach is accurate and robust and does not include time-consuming and memory-intensive impedance measurement tasks.

The microgrid operating cost can be minimised with a robust optimisation strategy of injected current by DERs. The estimated physical distance between DERs is an important factor to consider when dealing with the optimisation modelling of the current to be injected. The intelligent microgrid provides adequate communication and measuring infrastructure to solve this problem. The combination of power line communication for measurement and communication with estimating the distance base-time of the arrival of the signals in the communication infrastructure of the microgrid is an improvement. This creates a dynamic grid mapping estimation of the intelligent microgrid using power line communication. Furthermore, the time of arrival estimators using power line communication have more minor errors than wireless communication. Thus, the proposed model is for a specific context where the low complexity algorithm is needed for the energy thresholding principles [150].

5.5. Other Estimation techniques

The advent of innovative grid applications and technologies assists various applications in modelling the complexity of estimation techniques using diverse static methodologies. The advantage of innovative grid technologies is enabling dynamic state estimators for suitable monitoring, protecting and controlling modelling of power grid parameters and variables, as presented in Fig. 8. Those innovative approaches are developed in a wide range of DEG integration for the performance of microgrids, applying relevant implementation structures, as shown in Fig. 5, under diverse current types. Thus, a decentralised state estimation technique is formulated using a dual decomposition technique derived from the gradient and lagrangian relaxation method [1]. The methodology is applied to the recently emerging hybrid AC/DC smart microgrid. Thus, the solution developed in this scheme is accurate, converged and robust compared to the central state estimation technique. The approach also considers the phasor measurements, and with synchrophasor measurements, a linear single-phase approach formulates the AC and DC microgrids state estimation. The decentralised solution also improves data privacy. In [151], an intelligent centralised based-monitoring infrastructure and control scheme is designed to perform precise state estimation and expect to control the performance of the system. Kalman filter modelling is applied to formulate the proposed solution. Through the smart grid communication network umbrella, the centralised framework assists in developing a sustainable monitoring cyber-physical system. It is expected to set a distributed and efficient state estimation to solve the cyber-attack issue in future. However, the decentralised framework in [1] can offer an opportunity to handle cyber-attack matters due to its tremendous improvement in data privacy.

The conversion of the current of microgrids is wildly affected by disturbances and uncertainties. Apart from the Kalman filter technique, which is based on a stochastic filtering framework to estimate the system disturbances and uncertainties, there are several estimation techniques to increase the efficiency of microgrids. The Kalman filter technique avoids inaccuracy and instability of the design for the DC-DC converter by example. Some estimation methods to attenuate disturbances and uncertainties in the system are developed. These are extended state observer, higher-order sliding-mode observer, generalised proportional-integral observer, and non-linear disturbance observer [106]. Abhinav et al. [152] present a distributed estimation technique based on the least mean-square formulation to evaluate reference set points and mitigate the additive noise effect in communication interactions among microgrid inverters. A local least mean-square scheme is also developed to assess frequencies and voltages among neighbouring inverters. The noise impact is considered in the secondary control level for the voltage and frequency of inverters. Thus, an exploration of noise-resilient synchronisation of AC microgrids multi-inverter is determined.

In [24], a smooth variable configuration filter is presented. This estimation technique supports direct power control to evaluate the negative sequence currents and instantaneous feedback power. The methodology is combined with a cutting-edge exponential sliding mode control, as developed in [53], to coordinate a grid-connected operating mode of a microgrid. This estimation technique mitigates the detrimental impact of the negative sequence current injection and minimises the oscillation of the control and manipulated variables. Besides, the method provides an accurate estimation, which is possible with a reduced number of sensors as required in the standard estimation techniques. Other techniques are detailed in 5.5.3-5.5.4.

5.5.1. Discrete Fourier transform

An interpolated discrete Fourier transform is an estimation technique that provides precise analysis. The interpolated discrete Fourier transform technique estimates the voltage phasors of an innovative microgrid environment through the intelligent metering system. This method is applied under impaired conditions within abrupt voltage amplitude variations. However, regardless of the strongly impaired conditions of the system, the developed model performance with a careful selection of algorithm parameters provides the expected results [136]. A robust microgrid must handle various ragging conditions of the operation process, especially during all faults, such as bidirectional current faults and other faults caused by the amplitudes and raring of DGs. The discrete Fourier transform technique provides a classic and easy model to formulate the waveform distortion with an integer number of samples within the data window [153].

5.5.2. Least Square Technique

The parameter of the fault path for an intelligent DC microgrid is estimated by a least square technique (LST) using the intelligent electronic device [154]. The objective of the proposed strategy is to resolve the sensitivity and selectivity limitations of an overcurrent-based relaying system. It also provides an opportunity to tackle the challenging problem due to current limiting control in power converters and bidirectional power flow of ring configuration microgrid. The strategy applies the local data of current and voltage to avoid unexpected disconnection of VERs and discriminates the system protection of microgrid under various fault situations. Therefore, the designed method provides more accurate results compared to available techniques.

LST proves its ability in several estimation strategies of faults assessment of microgrids. In [155], adaptive Kalman filer and LST are combined to handle state and parameter estimation of fault detection on DC microgrids. The strategy develops a recursive LST to identify and detect series arc faults in the line accurately. In [153], it is found that the LST is more suitable for AC microgrid fault detection and protection than the discrete Fourier transformer and Kalman filter. Ref. [156] shows that a recursive LST can suitably be formulated as an islanding detection method to estimate the frequency of active off-grids effectively. The protection scheme of DC microgrids is increasingly needed to handle their rapid growth due to their design simplicity and cost-effectiveness. The most faults of DC microgrids are low-impedance and high-impedance faults. Therefore, the LST can solve these problems by detecting the high impedance fault without any communication link on the system [157].

5.5.3. Optimal Management Technique

The optimal management technique (OMT) applies an optimisation approach to creating an estimation scheme to resolve the diverse uncertainty of microgrid operation. This can also be seen as an estimation technique to monitor the accuracy of a microgrid. Deterministic, stochastic and robust optimisation strategies are the principal schemes that deal with microgrid-based-OMT system uncertainty. The most significant problems of OMT are discomfort minimisation, economic dispatch, energy cost minimisation or congestion management, monitoring and control of energy, pollution minimisation, and unit commitment [9]. OMT has the advantage of being developed in a different framework that can suggest opportunities to deal with system disturbance and uncertainties. In [158], a novel optimal scheduling method is presented to reduce the isolated microgrid operating costs. The model used OMT to coordinate the DERs with the system uncertainty of spinning reserves derived from ESS.

A framework to cluster three interconnected microgrids is presented in [159]. The strategy designs a microgrid cluster with the combination of three methods. Firstly, the storage agent replaces the optimisation technique to intelligently estimate battery throughput, which can accurately corroborate the microgrid replacement cycle. Secondly, an intelligent energy routing algorithm is applied to efficiently utilise and capture excess power from VRE to share within clustered microgrids. Finally, an energy storage optimisation technique improves the design of clustered microgrids by resizing the storage component. Based on the first strategy, this framework can be considered an estimation technique applied to microgrid modelling. The combination of three methods can classify the framework as an estimation technique based on OMT. Ref. [160] presents an intelligent estimation technique based-deep learning to estimate the SOC of BESS in conjunction with VRE coordination with hybrid EVs. The estimation of BESS is essential for microgrids, and an OMT can provide several approaches to optimise the BESS charging and discharging process. This is because the ESSs, including EV and conventional BESS, are the future of the modern power grid environment [161]. Besides, deep learning strategy, in fact, most ML methods, is currently seen as one of the most robust methods to be formulated in various ranges of power system applications, including OMTs [162].

5.5.4. Forecasting Technique

The random variation of RERs negatively affects the efficient operation of microgrids, especially in an islanding mode. The forecasting techniques assist in dealing with the uncertainty on both demand and VRE sides [9]. The resource forecasting of VERs, such as solar and wind powers, are essential factors in avoiding unexpected failure of microgrids [163]. In addition, estimating VRE potential is vital for increasing the predictability and profitability of RERs [164]. This can optimally assist in improving the efficient operation of an intelligent microgrid [130].

AI can play an essential role in forecasting microgrid load demand [165]. ML applications in the intelligent grid have a broad range of implementation domains, including load and price foresting, VRE prediction, fault assessment (detection, classification and location), distribution, generation and transmission management systems, etc. [162]. An ML-based-deep reinforcement learning is developed to handle scheduling and single-step multi-period forecasting for microgrids [166]. The developed semi-supervised ML model deals with a sequence operation theory and addresses the system uncertainty to predict an accurate forecast and then schedule the demand response behaviour to minimise the operating cost of microgrids. Ref. [167] presents estimation techniques to predict the wind power potential by incorporating the atmospheric response. The developed method uses a kinetic energy budget approach to assist the policy applications because it has a lower estimation than the current standard strategy. This strategy aims to determine the best location for installing DERs and the time to use the full potential of VREs.

6. DISCUSSION AND FUTURE VISION

The novel vision of control structure, hybrid control, as presented in Fig. 5, of a microgrid aims for innovative approaches to build an autonomous power grid development, where the power network can operate between Phases 4-5, as presented in Fig. 2. The benefits of microgrids, detailed in Fig. 1, show that the autonomous operation of such systems is eventual. Therefore, microgrids viably enable an intelligent grid environment of an electric network. The integration of various autonomous systems in one encompassment requires robust and resilient control, monitoring and protection techniques. Thus, multi-agent systems (MASs) emulate a dynamic behaviour of concerting various stakeholders in diverse applications [168]. MASs cooperates with multiple actors in the energy sector, including DERs, end-users, distribution system operators, transmission system operators, generation system operators, auxiliary services, etc. MASs have bred multi-energy systems through the use of innovative technologies. For instance, integrated demand response based on energy internet in the framework of the IoT [169] is one of the advanced demand response strategies to design a multi-energy system [170]. A simple microgrid is an excellent conceptual instance of MAS where several independent DERs are coordinated through a distributed control structure neighbourhood. Thus, the communication network prefigures the efficient operation of MAS [171].

Figure 9 presents the 5Ds (decentralisation, decarbonisation, democratisation, deregulation and digitisation) vision for the future power grid implementation. This concept can be seen as the backbone of the optimal control design of smart microgrids. Several published research works look to respond to at least one or more D of this concept. For instance, climate change aims to support net zero and achieve sustainable development goals using more than one D of 5Ds vision [48]. VRE is one of the efficiency schemes in smart microgrids used to support net zero. Besides, control and estimation techniques applied to microgrids possess the innovative approaches that make 5Ds visions a reality within the perspective of reaching Phase 5, as presented in Fig. 2. Besides, the efficient operation of microgrids should always be designed applying MAS conceptual framework to satisfy all stakeholders and policymakers working to achieve 5Ds visions.

6.1. Discussion

Table 4 summarises different control techniques in smart microgrids. It should be noted that data-driven methods are the other appellation to describe soft computing techniques. A soft computing technique refers to diverse, intelligent strategies based on evolutionary computation and data-driven. Besides, Data-driven is known as the application of data sciences to emulate the behaviour of optimal control strategy. This usually refers to AI and ML. This is one of the powerful techniques that will make the future generation of the power grid an autonomous electrical network, as presented in Fig. 2, and efficiently allow the application of MASs. The estimation techniques are formulated within some specific boundaries, which are based on smoothing (past), filtering (present) and prediction (future) of the system. The formulation of the estimation techniques and/or approaches is based on the design frame presented in Fig. 8. Table 5 assesses some observations based on their specific implementation concept.

Some deterministic optimisations are mostly built on an adequate optimal control approach to handle the dynamic tertiary control performance of microgrid 4. A stochastic optimisation strategy can also design an optimal control scheme. Still, it will be better classified as a combination of control and estimation techniques due to its ability to consider the different uncertainties of the system. Deterministic optimisation-based-optimal control schemes can be classified in the range of linear or non-linear control techniques depending on Eqs. 16 and 18, respectively. Besides, either optimisation control scheme-based-deterministic or stochastic optimisation can be designed based on a control and/or estimations technique framework.

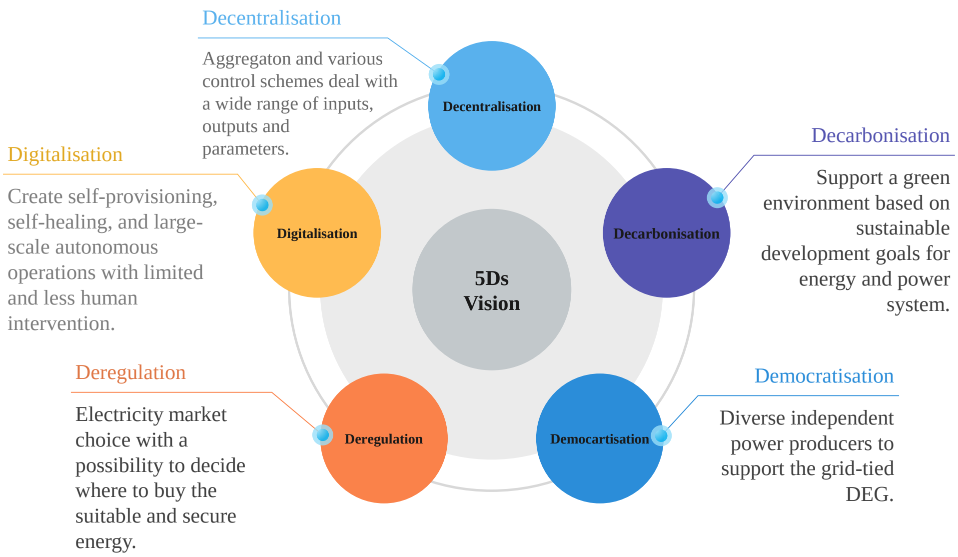

Figure 9: Innovative Microgrid implementation: 5Ds vision.

Table 4: Trend for recent control techniques applied in smart microgrid.

Refs.	Year	Control Technique	Control Approach	Observation based-Application and Major Contribution
[172]	2022	Adaptive	PI Controller	Centralised microgrid PI based on single-perceptron and least mean fourth controllers for the islanded microgrid to guarantee power-sharing.
[173]	2022	Intelligent	Takagi-Sugeno fuzzy model	Develop a generalized predictive control (GPC) strategy based on fuzzy mode for optimal load frequency control of two-area to enhance the system performance compared to simple GPC and PI.
[174]	2022	Predictive	MPC	Active power control based on predictive control technique to control the load frequency and area error within the tie-lines by applying the ESS. This is a secondary control to compare the MPC performance with the feedback control strategy based on a linear model.
[175]	2021	Intelligent	ML and AI	Regression-based learning tool is developed to create a data-driven strategy to control a voltage source inverter of a grid-connected microgrid. This scheme looks to enhance the accuracy of the system and interpret the uncertain results.
[176]	2021	Linear	Derivation Voltage control	Ensure stability by misnaming the sensitivity during load conditions and voltage reference to mitigate the non-linear terms of an equivalent circuit for a duo active bridge converter.
[177]	2021	Intelligent	Based Communication	Assess different IoT protocols for real-time microgrid operation control, monitoring and protection.
[178]	2021	Predictive	MPC	Use a non-linear control scheme to address the current control of the multilevel converter to supply intelligent load and improve power quality and reliability.
[179]	2021	Robust	Droop Control	A smooth solution for multi-source microgrid power balance based-voltage and frequency control with the communication-free system under decentralised and primary control.
[180]	2021	Adaptive	Consensus control	To accurately share the harmonic and improve the voltage quality. Suitable for complex feeder networks and variable structures, this scheme does not require a complete picture of the system.
[181]	2020	Non-linear	External droop	A hierarchical framework to control frequency and voltage at the PCC of networked microgrids. A DER primary control layer is applied.

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Table 4 – continued from the previous page.				
Refs.	Year	Control Technique	Control Approach	Observation based-Application and Major Contribution
[182]	2020	Intelligent	Soft Computing	Machine learning (deep learning and neural networks provide) is the primary driver for smart microgrid trends to effectively address the diverse challenges of intelligent grids.
[183]	2020	Predictive	MPC	Centralised control system to coordinate network microgrid and coordinate water and electricity for the end-users. This system deals with various uncertainties in RES and demand.
[184]	2020	Robust	H∞ consensus	To accurately regulate microgrid voltage and frequency, controlling the proportion of active power-sharing and modifying the BESS SOC.
[185]	2020	Intelligent	Soft Computing	Apply multi-agent and multiobjective-based-reinforcement learning to deal with load frequency control and economic dispatch of microgrids.
[116]	2020	Intelligent	Recurrent probabilistic wavelet fuzzy NN	Develop a central strategy based on master-slave control to apply intelligent control technique to improve reactive and voltage controls while guaranteeing the smooth shift of microgrids.
[186]	2019	Linear	Quadratic regulator	Primary and secondary control loops for an interconnected microgrid are presented to formulate a distributed optimal control structure with a load frequency control strategy that can coordinate the power-sharing of an interconnected network system.
[187]	2019	Non-linear	Droop control	Active and reactive-power sharing coordination using a hierarchical control method based-primary and centralised control for optimal power flow of microgrid.
[188]	2019	Predictive	MPC	Two-layer EMS based-hierarchical control for economic dispatch using a consensus algorithm and replicator dynamic to solve the linearity of the marginal performance index.
[189]	2019	Adaptive	Hybrid, PI, droop and sliding mode	Eliminate the current-sharing error, regulate DC bus voltage and coordinate each input current and output voltage of converter for a networked microgrid.
[190]	2018	Linear	Droop control	Apply Riccaty equation to model a novel current controller to improve the seamless transition for off-grid operation and resynchronisation of grid-tied microgrid.

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Table 4 – continued from the previous page.				
Refs.	Year	Control Technique	Control Approach	Observation based-Application and Major Contribution
[191]	2018	Predictive	MPC	Regulate the system voltage and alleviate the power loss in the distribution system for DC microgrid with electric springs. A centralised MPC is applied.
[192]	2018	Adaptive	hybrid control	Apply predictive control into a combined artificial neural network and fuzzy logic to increase the application of DERs, control power-sharing and reduce the power from the utility grid.
[193]	2017	Predictive	Dead-beat	Current control for converters with an independent current regulator, and compensator for frequency estimation.
[194]	2016	Predictive	MPC	Coordinate multi-microgrid for power system resilience to create hierarchical outage management and satisfy and avoid natural disasters on the distributed system operator side.

Table 5: Assessment trend of estimation techniques.

Refs.	Year	Smoothing	Filtering	Prediction	Observation
[160]	2022	✗	✗	✓	Apply data-driven scheme based-deep learning for energy coordination system under a hybrid convolution NN and long short-term memory method accurately estimate the SOC of battery.
[172]	2022	✗	✓	✗	Formulate the Gauss-Newton based on recursive filters to estimate the harmonic and voltage fundamental at the demand side to support the central adaptive control techniques for efficient power-sharing.
[195]	2022	✗	✗	✓	Wind energy potentials estimation by considering the minimisation in mean wind speeds caused by the extraction of Kinetic energy to minimise the system complexity.

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Table 5 – continued from the previous page.					
Refs.	Year	Smoothing	Filtering	Prediction	Observation
[196]	2021	✗	✓	✗	Kalman Filter algorithm is used to accurately estimate the power compared to measurement power to improve integral synergistic control combined with direct power control.
[197]	2021	✗	✗	✓	Applied ML-based ANN for fault diagnosis and demand forecasting. This is seen as an effective monitoring tools and predictive strategy to guarantee the reliability of microgrid.
[198]	2021	✗	✗	✓	Use NN for a symbiotic organism search algorithm as a new optimisation scheme to determine the values of lower and upper estimation parameters for an excellent prediction interval and high confidence level.
[199]	2019	✓	✓	✗	Data-driven technique is used to combine discrete wavelet transform and Taguchi-based ANN for faults classification, detection and location of a microgrid.
[54]	2019	✗	✓	✗	Kalman filter to support the direct power control of DEG for accurate voltage and power estimation. The developed model applies the super-twisting method to handle the direct power strategy.

Tables 4 and 5 present the most relevant research works during the last half-decade that deal with control and estimation techniques for an intelligent microgrid. This shows how several approaches can be implemented using different techniques. Finally, Figure 10 describes a fundamental concept to consider for the efficient design of control and estimation techniques. This shrewdness introduces a sub-primary layer, added from the conventional layer scheme as presented in Fig. 4. The sub-primary layer assists with optimal control and estimation of DEG for an accurate and efficient operation of smart microgrids, which require an accurate assessment of potential power from DERs. The sub-primary layer also determines the best installation location of DERs with reasonable potential yield and possible lowest resource uncertainties.

The bandwidth and time scale of the control hierarchy are inversely proportional to microgrids primary to tertiary control level. This means primary control requires high bandwidth in a lower time scale computation, while tertiary control structure needs a low bandwidth in a higher time scale [9]. In addition, semantic technologies are used in innovative grid environments for accurate

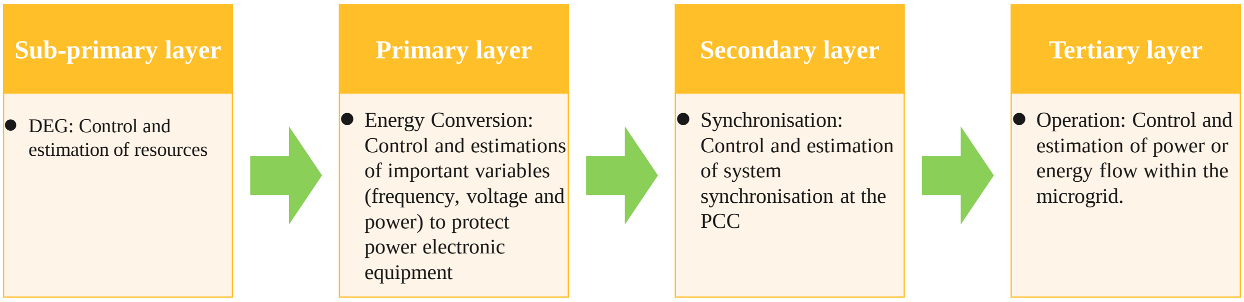

Figure 10: Perspective of microgrid Control and estimation techniques development and implementation.

estimation and efficiency at run-time [200]. It is essential to note that the manipulated variable of operating microgrids depends on the state and control variables for appropriate optimal control behaviour. The output reference is one of the significant variables to track for a suitable performance and a robust operation of off-grid and grid-connected microgrid modes [18]. Therefore, a reasonable selection of control and estimation methodologies is essential for an efficient operation of a smart microgrid.

The difference between the control approaches and control techniques depends on their applications. The control approaches can be applied in one or more specific control layers, as detailed in Fig. 10. In comparison, the control techniques can be designed in every control layer depending on the dynamic of operating microgrids. Throughout the evolution of dynamic modelling methodologies, some control approaches, such as active and reactive power control, droop control, frequency and voltage control, etc., can sometimes be identified as control techniques. The system analysis and system design offer a benchmark of opportunities to design any control methodology using all discussed control techniques from 4.1-4.6. In [14], an exceptional hierarchical control model for the microgrid is presented, which contains the main layers detailed in Fig. 4. However, the developed model has contributed to the control aspect of the AC microgrid based on three layers, which started with internal control loop to perform the source operating point control, such as maximum power tracking of VRE. Thus, the proposed perspective to increase the efficient operation of microgrids, as depicted in Fig. 10, gives both the most crucial aspect for control and estimation techniques of intelligent microgrid operations, regardless of their types, structures and configurations of a microgrid network.

6.2. Future Vision

Figure 11 is an advanced version of Figs. 9-10 to reflect the implementation conceptualization of control and estimation techniques based on the digital transformation journey of the smart grid, as presented in Fig. 2. This advanced version devises a digital thread model of a smart microgrid environment. From Figure 11, it can be seen that it is inordinately assertive to use only one microgrid to achieve energy trilemma goals. However, the 5Ds vision demonstrates that implementing innovative technology illustrates an opportunity to compass an affordable, clean and secure energy system. Therefore, the digital thread concept also considers that the novel generation of the power network, which will be based on combining microgrids, is only a MAS operating network.

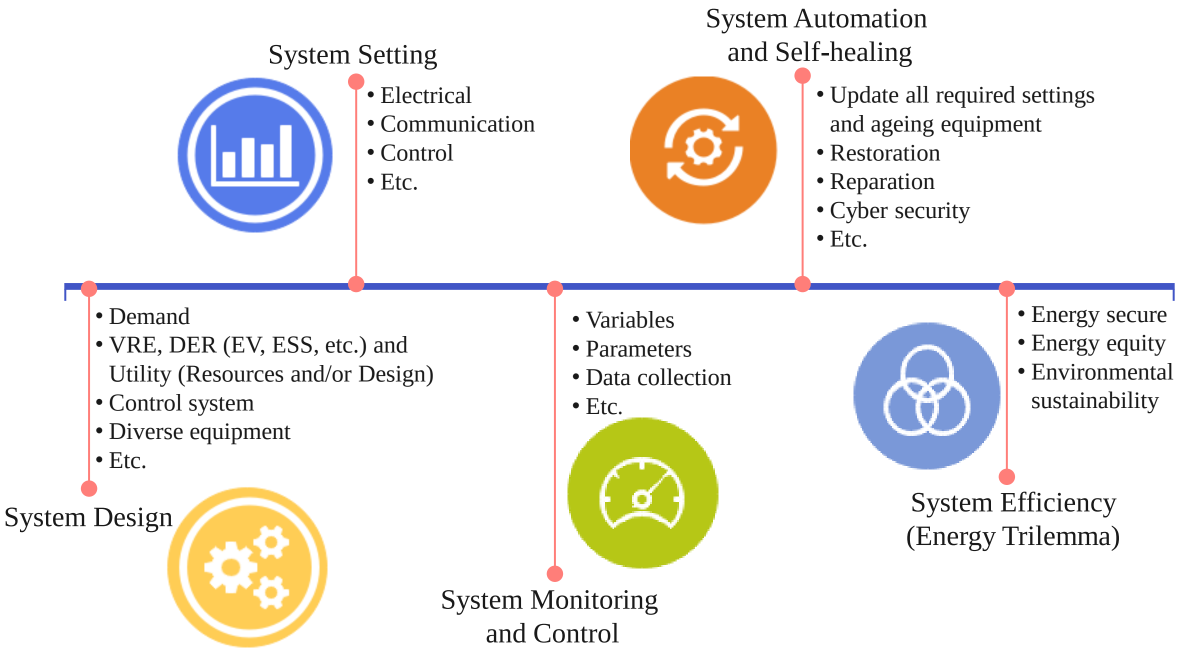

Figure 11: Digital thread of microgrid control and estimation techniques.

Moreover, the future of microgrids requires control techniques that can autonomously carry any dynamic concept illustrated in Fig. 4 and accurate state estimators to handle the protection and monitoring of parameters and variables detailed in Fig. 8. Thus, microgrids can operate at Phase 5 of Fig. 2.

The estimation techniques support the control schemes of microgrids. A suitable combination of estimation and control approaches robustly manages all system variables [140]. The intelligent grid environment introduces an excellent variety of control and estimation of the power network. This environment makes the power network robust by enabling bidirectional communication between control centres, intelligent electronic devices, phasor measurement units and remote terminal units. Data accuracy is essential when dealing with the collaboration of novel power generation with the increasing real-time decision-making by sensors. However, the intelligent microgrid is vulnerable to cyber-attacks where a well-crafted attack can inject false data into the microgrid during the state estimation and affect the operation and control of the electrical system [201] with serious techno-economic, and social problems [47]. The conventional techniques, such as Newton-Raphson, for protecting some critical sensors within the microgrid can alleviate the impact of false data injection attacks. A hacked meters identification strategy is one of the best techniques to eradicate all penitential threats to the power system [201]. As detailed in Fig. 11, the perspective intelligent microgrid operation should rapidly localise false information and adapt the process based on dynamic behaviour.

The energy internet is an advanced concept in the smart grids [36, 169]. This can be efficiently modelled through a hybrid control structure based on the vision of innovative microgrid control implementation, as presented in Fig. 4. However, the energy internet is based on distributed architecture to balance the power network. Therefore, the system can independently operate from the main transmission and distribution network, as explained in [36]. Nevertheless, this architectural configuration looks mostly to DERs with the possibility of large size of ESSs and probably with an aggression number of EVs integration, and differs from to control structure, as detailed in Fig. 5. Besides, implementing robust and resilient control and estimation techniques in intelligent grid scenery will be challenged to diverse aspects, parameters and variables. The most significant challenge is developing a system operating within the 5Ds vision. Therefore, prospects are to design a system that can respond to all requirements, as presented in Fig. 11. These will include a hierarchical model for system control, monitoring and protection to handle fault detection and location, self-healing, cyber security, resources and states estimations, delay less or instantaneous communication network with fast and real-time data transfer within a MAS conglomerate, etc., and satisfy all stakeholders while providing an energy trilemma environment.

7. CONCLUSION

Innovative grid technologies have transformed the system modelling and design of the power grid. These technologies come with novel concepts for two-way communication and opportunities to manage the energy flow from different independent agents efficiently. The smart grid can be summarised as the combination of DERs integration and optimal control techniques. Microgrid deployment is the conceptual platform that makes the implementation of intelligent technologies possible. An innovative microgrid operation requires hierarchical coordination with different technologies to control and estimate various variables and parameters in a real-time environment, regardless of the system complexity, types, and structure. It is often difficult to differentiate the control approaches or modelling of microgrids in the innovative grid environment. This research work assesses different control techniques for innovative microgrids. The estimation techniques are also addressed to perfect the vision of an efficient microgrid operation.

The study classifies the control techniques into six categories: linear, non-linear, robust, predictive, intelligent and adaptive control techniques. This control classification aims to assess their intrinsic implementation performances within the dynamic design and modelling structure, layers and approaches of innovative microgrids. It has been observed that some control techniques can be implemented within a framework that emulates two or more methods. Besides, some strategies have been considered techniques in most relevant published research works. However, the classification of this research demonstrates that these strategies are within the six control techniques categorisation. The hierarchical control described the primary, secondary and tertiary microgrid layers for efficient operational performance. This also added a sub-primary layer that looks at the reasonable estimation of DERs potential as microgrids are the powerhouse of DERs implementation. In addition, the microgrid controllers are, in most scenarios, a combination of hierarchical control layers to stabilise, regulate, improve, and coordinate the system behaviour. In this research, a novel control structure, namely hybrid, has been introduced to stand out from the most relevant control structures. These are centralised, decentralised and distributed control structures. The hybrid control structure is the combination of all three appropriate control structures. This is the perspective of the overall autonomous electric network constituted by MASs.

An effective hierarchical control design necessitates excellent monitoring behaviour to protect microgrids against unexpected events. Therefore, various estimation techniques applied to support the operation of microgrids are also addressed. These are state estimators-based amplitude, frequency or angle and phase measurement. Besides, the estimation techniques review the modelling methodologies that estimate real-time resources and equipment performance. The monitoring of resource uncertainty and ageing equipment permits avoiding unnecessary losses on the dynamic system operation of the microgrid. In addition, the location methods protect the overall system against diverse abnormal issues, such as faults and cyber-attacks, and also provide an opportunity to determine where installing DERs to improve the system performance. Besides, it has been observed that the sub-primary layer is necessary for the overall performance of microgrids where the uncertainty of DERs is repeated in most scenarios. The sub-primary layer is also the most suitable prospect to determine where the DERs can be installed.

Furthermore, microgrids are not yet commercialised, and their innovative implementations must reach the future of the digital transformation journey of the smart grid, which is based on an autonomous system that entails the 5Ds vision to satisfy all stakeholders. Moreover, a framework-based digital thread for designing and modelling control and estimation techniques is proposed to offer a hierarchical guideline for smart microgrids. This digital thread architecture provides a perspective to shape the digital twin of intelligent microgrids and guarantee the innovative implementation of 5Ds vision for autonomous power networks.

Future research works will explore hierarchical coordination vision perspectives of innovative microgrids. These works will focus on independently assessing different control and estimation techniques combinations to determine optimal hierarchical solutions in developing and implementing autonomous power networks. Besides, a digital twin architecture-based MAS will be extended to promote the commercialisation of microgrids and support the 5Ds vision.

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