Battery and energy management system for Vanadium Redox Flow Battery: A critical review and recommendations

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Abstract

As one of the most promising large-scale energy storage technologies, vanadium redox flow battery (VRFB) has been installed globally and integrated with microgrids (MGs), renewable power plants and residential applications. To ensure the safety and durability of VRFBs and the economic operation of energy systems, a battery management system (BMS) and an energy management system (EMS) are inevitable parts of a VRFB-based power system. In particular, BMSs are essential to conducting efficient monitoring, control and diagnosis/prognosis functions with the help of a feasible and comprehensive battery model. Considering the application of a VRFB is normally integrated within a grid-level system, an EMS is required to operate the entire system in coordination with the BMS optimally. Several papers have reviewed the design and modelling of VRFB recently. However, the BMS and EMS in VRFB applications have received limited attention in the literature. This review article introduces the principles, applications, and merits of VRFBs and presents a critical review of the state-of-art VRFB modelling techniques related to BMS and EMS operation. More importantly, the state-of-the-art BMS for VRFBs is reviewed by taking the unique design of the VRFB systems into account, and recommendations are given for future development. Finally, several VRFB EMSs are discussed to illustrate their importance in improving the stability and reliability of grid-level power systems.

Keywords: Renewable energy, vanadium redox flow battery, battery modelling, battery management system, energy management system.

Nomenclature

V^{2+},VO^{3+},VO^{2+},VO_2^+ Vanadium redox species

AI Artificial intelligence

ALO Ant lion optimisation

ANN Adaptive neural network

BE Battery efficiency

BFOANN Bacterial foraging optimisation - artificial neural network

BMS Battery management system

C Capacitance (F)

CAES Compressed air energy storage

CC Constant current

CE Coulomb efficiency

CSTR Continuous stir tank reactors

CV Constant voltage

DAQ Data acquisition

DER Distributed energy resource

DG Distributed generation

DNN Deep neural network

DP Dynamic programming

ECM Equivalent circuit model

EKF Extended Kalman filter

EM Electrochemical model

EMS Energy management system

ePCDNN Enhanced physics-constrained deep neural network

ESS Energy storage system

EV Electrical vehicle

FC Fuel cell

FC-ASCC Fuzzy-controlled active state-of-charge controller

FES Flywheel energy storage

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FLC Fuzzy logic controller

GOAPSNN Grasshopper optimisation algorithm Pi sigma neural network

HEKF Hybrid extended Kalman filter

HIF H_∞ filter

HMI Human-machine interface

HVAC Heating, ventilation and air conditioning

I Current (A)

IEKF Improved extended Kalman filter

IMG Islanded microgrid

IoT Internet of things

IS Industry-scale

KF Kalman filter

LCOE Levelised cost of energy

MG Microgrid

MILP Mixed-integer linear programming

MPC Model predictive control

MPPT Maximum power point tracking

NaS Sodium-sulfur

NN Neural network

OCV Open circuit voltage

ODE Ordinary differential equation

OPV Organic photovoltaic

P&O Perturb & Observe

PCDNN Physics-constrained deep neural network

PCS Power conditioning system

PDB Photovoltaic-diesel battery

PF Particle filter

PFR Plug flow reactor

PHES Pumped hydroelectric energy storage

PMS Power management system

PNN Probabilistic neural network

PSO Particle swarm optimisation

PV Photovoltaics

R Resistance (Ω)

R&D Research and development

RBFNN-SSA Radial basis function neural network- slap swarm algorithm

RC Resistance-capacitance

RES Renewable energy sources

RF Random forest

RFB Redox flow battery

RFCRO Random forest coral reefs optimisation

RLS Recursive least square

SC Super-capacitor

SE System efficiency

SEI Sumitomo Electric Industries

SMO Sliding mode observer

SOC State of charge

SOH State of health

TCU Temperature control unit

TES Thermal energy storage

TMS Thermal management system

TTF-RLS Time-varying forgetting factor recursive least square

UKF Unscented Kalman filter

UNSW the University of New South Wales

V Voltage (V)

VE Voltage efficiency

VRFB Vanadium redox flow battery

Subscripts

ch Charge

diff Diffusion

dis Discharge

f Flow

rea Reaction

res Resistance

1. Introduction

Due to the rapid growth of renewable energy sources (RES) in recent years in response to policies and actions against climate change, the amount of energy produced by RES has grown exponentially [1]. While RES offer competitive advantages over alternative energy sources, such as low production cost, abundance, sustainability and environmental friendliness. However, they are weather dependent; thus not always available, and it is difficult to accurately predict their output at different timescales [2]. Moreover, electricity grids have become vulnerable due to the intermittent generation and undispatchability of RES, which decreases their stability and reliability in electricity distribution [3]. Thus, an electricity grid with a large share of RES requires more flexible resources to compensate for variability at different timescales.

One popular and promising solution to overcome the above-mentioned problems is using large-scale energy storage systems to act as a buffer between actual supply and demand [4]. According to the Wood Mackenzie report released in April 2021 [1], the global energy storage market is anticipated to grow 27 times by 2030, with a significant role in supporting the global energy transition to green and sustainable energy. Depending on the application, various energy storage technologies can be deployed, e.g., flywheels for short-term applications and hydrogen for seasonal variability applications. Therefore, integrated RES and large-scale energy storage systems are necessary to operate and maximise the efficiency of an electricity grid with high amounts of RES [5]. Among various types of energy storage systems, large-scale electrochemical batteries, e.g., lithium-ion and flow batteries, are finding their way into the power system, thanks to their relatively high energy density, flexibility, and scalability [6]. Different battery technologies are proven suitable for various power system applications, mainly including lithium-ion batteries, lead-acid batteries, redox flow batteries, sodium sulphur batteries, etc. Among these batteries, the vanadium redox flow battery (VRFB) is considered to be an effective solution in stabilising the output power of intermittent RES and maintaining the reliability of power grids by large-scale, long-term energy storage capability [5].

The VRFB was first developed in the 1980s and has been commercialised in the past 10 years [7]. The VRFB is more flexible in capacity expansion and design compared with lithium-ion and lead-acid batteries by increasing the volume of electrolytes and the electrode size. Moreover, VRFBs offer a longer lifespan, simpler structure, deep cycling, and low degradation. In terms of structure, VRFBs are made of several replaceable components, which result in a low operational and maintenance cost after setting up. All the above-mentioned advantages make the VRFB a practical and competitive solution for coupling with intermittent RES in microgrids (MGs) and renewable power plants [8]. In the last decade, several trials around the globe have demonstrated the capabilities of VRFBs as reliable and efficient energy storage systems (ESSs) within power grids with single or multiple RESs [9, 10, 11, 12]. Moreover, large-scale VRFBs have been installed worldwide with capacities from a few 100 kWh to several MWh [13]. For instance, a 200 kW/800 kWh VRFB was installed in a power station in Japan for load-levelling, which was the first medium-scale VRFB field trial [14]. The trial has shown the extraordinary performance of the designed VRFB stacks without having any performance degradation after 12,000 cycles and achieved an overall efficiency of 80% [14]. In 2005, Sumitomo Electric Industries (SEI) installed a 4 MW/6 MWh VRFB at the Tomamae wind farm in Hokkaido to smooth the turbine output power and to increase wind farm reliable operation, where the battery experienced 200,000 cycles [14, 15]. A review of medium- to large-scale VRFB installations is provided in [14] that contains information from 2001 to 2012 collected from Japan, the USA, Denmark, China, Indonesia, India, and Netherlands [14]. With the rapid acceptance of the technology by the power industry, large-scale VRFBs are becoming more popular. China is leading on that front with the recent installation of 200 MW/800 MWh and 100 MW/ 500 MWh VRFBs in the city of Dalian and Hubei province, respectively, [16, 17]. Figure 1 shows a global map of medium- to large-scale VRFB installations worldwide until May 2019. It is evident that the commercial sector realised the potential of VRFBs in various power system applications, including energy shifting, peak shaving, and power arbitrage [14].

Nevertheless, compared to lithium-ion batteries, VRFBs have lower energy density, lower round-trip efficiency, higher toxicity of vanadium oxides and thermal precipitation within the electrolyte [2, 19]. To address these issues, fundamental research has been carried out on the battery working principles and internal chemical processes to enhance the materials, design and operation of VRFB's core components, e.g., electrolyte, electrode, membrane material and stack design. Many publications have demonstrated new research outcomes in the material selection and design of VRFB, which aims to enhance the overall efficiency, energy density and flexibility in operation. Interested readers are referred to [20, 21, 22, 23, 24, 25] on the study of advanced membranes, [26]-[27] on recent development of commercial membranes, [28, 29, 30, 31] for studies on new electrode materials, and [32, 33, 34] on new electrolyte compositions. However, these studies focused on improving the performance of VRFBs in the design and manufacturing stages. Still, more advanced strategies and controllers are necessary to adapt to the operational requirements of different applications while enhancing overall efficiency and reducing operation and maintenance costs. Moreover, simulations and laboratory-based experiments on VRFB cells are important to accurately predict large-scale VRFB operation and allow in-depth analysis of the improvements of different materials [7]. Currently, simulation models of VRFB are used to estimate and monitor the system states and allow automated control during operation. These controllers are designed to improve the long-term stability and efficiency of VRFB systems, considering the hydraulic system pressure drop through flow rate optimisation, charge current optimisation, temperature management, and electrolyte rebalancing techniques [35, 36, 37, 38]. Equivalent circuit models (ECM), electrochemical models (EMs), hybrid models and AI-based battery models are the four categories of models developed by researchers throughout the last decade or so.

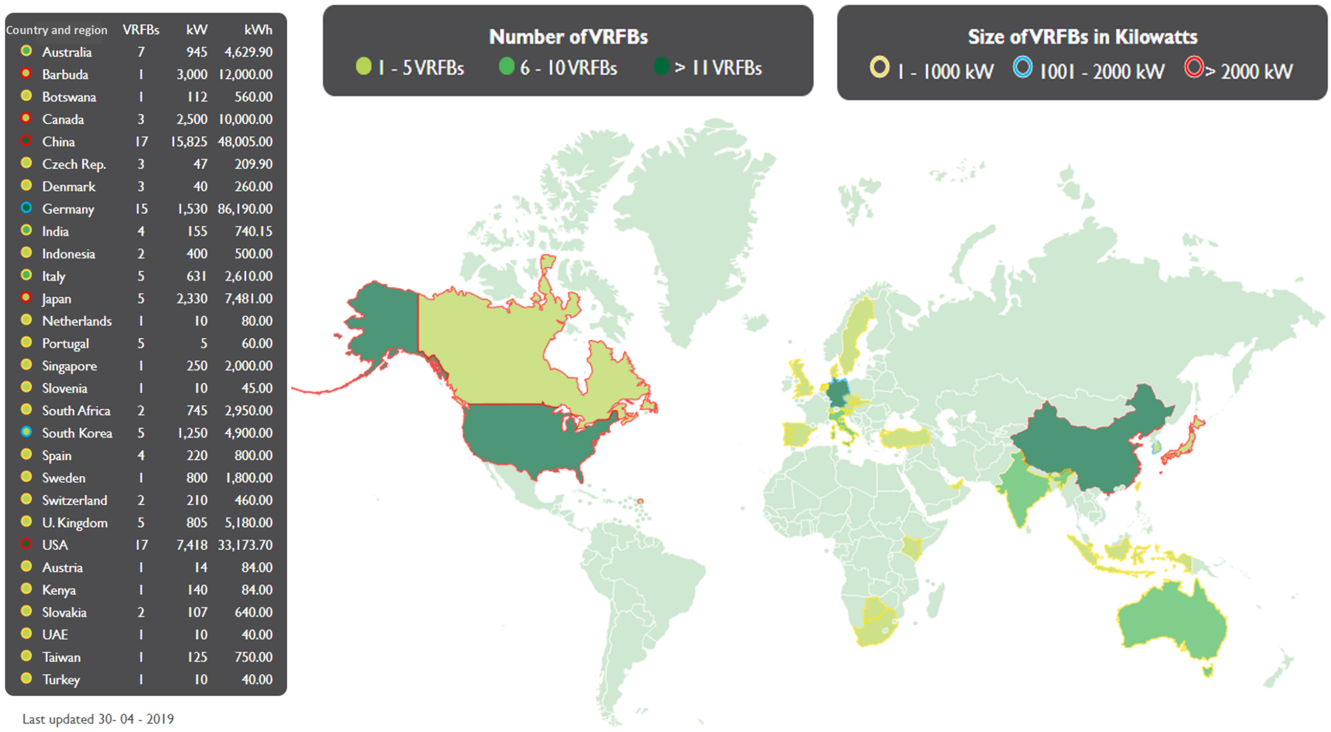


Figure 1: Global VRFB installations map from VANITEC – last updated on 30/04/2019 [18]

As with any battery technology, VRFBs require a suitable battery management system (BMS) that takes into account the properties of the battery and operates it in the most cost-effective and reliable fashion [39]. A BMS normally consists of various sensors, actuators, controllers, signal processors and smart operational algorithms to ensure the battery's safe operation and enhance the system's efficiency and reliability. Tremendous efforts have gone into developing BMS for lithium-ion batteries. However, only a few papers and reports have been published on a detailed BMS design and battery management scheme for VRFBs. As indicated in [40], despite many studies and extensive reviews of papers on VRFBs that have been published in recent years, the literature on engineering aspects of VRFBs management and operation is limited. In [41], an industry-scale VRFB (IS-VRFB) is proposed to fulfil this research gap with a detailed description of the hardware and software implementation of a VRFB-BMS. However, this study does not provide information about the battery management operational algorithm. Additionally, considering the VRFB application in MGs, RES plants etc., where the VRFB is a part of a larger system, the uncertainty, intermittency and unpredictability of a complex power system and their impacts on the VRFBs operation and performance must be studied [42]. In this case, energy management systems (EMSs) are developed to handle the supply and demand requirements while considering the system constraints to achieve a sustainable and reliable operation of MGs and other power systems under set objectives [43]. Unlike the VRFB-BMS, which only considers the battery, an EMS takes the whole power system into account to make the best decisions based on cost and benefits while considering the physical limits of the system and equipment and reliability. Different EMSs have been developed in [44, 45, 46, 47, 48, 49] using different exact and metaheuristic optimisation techniques for islanded and hybrid MGs, which showed improvements to increase the stability and economic benefits. However, the main focus of these studies is managing the entire system; thus, they do not give enough attention to the VRFB requirements and physical limitations, e.g., thermal precipitation of vanadium species, vanadium ion imbalance and hydrogen evolution, which deteriorate the performance of VRFBs [50]. It can be seen that more research and developments considering the practical limitations of VRFBs are needed to establish a comprehensive BMS that aligns with EMS operations aiming to maximize VRFB efficiency. This is critical to mitigate risks at the battery level and to operate the system most cost-effectively.

This review paper is organised as follows: a brief introduction to VRFB design and operation is presented in Section 2. Then, different applications of VRFB are introduced in this section, and the challenges of developing VRFB are identified. In Section 3, the importance of VRFB modelling and a review of mainstream VRFB modelling techniques are presented and analysed. Section 4 elaborates on the VRFB-BMS scheme with seven functionalities to properly manage the battery operation. Current VRFB-BMSs are reviewed, and advanced techniques are recommended to improve their performance. Finally, in Section 5, several VRFB-related EMS are reviewed, and the importance of EMS for power systems is emphasised. A cooperative BMS-EMS scheme is proposed to ensure the sustainable development of a power which contains VRFBs.

2. Overview and applications of VRFB

2.1. VRFB overview and working principles

The VRFB is commonly referred to as an all-vanadium redox flow battery. It is one of the flow battery technologies, with attractive features including decoupled energy and power design, long lifespan, low maintenance cost, zero cross-contamination of active species, recyclability, and unlimited capacity [51, 15]. The main difference between flow and solid-state batteries is that the electrolyte is stored in the tanks in the VRFB. The electricity is produced from chemical reactions within the electrolyte. As shown in Fig. 2, the VRFB normally contains two separate electrolyte reservoirs (tanks). These two reservoirs store vanadium solutions with four different oxidation states (V^{2+}, V^{3+}, VO^{2+} [same as V^{4+}] and VO_2^+ [same as V^{5+}]) with the benefits of having single electromotive element. The positive side refers to the positive electrode and tank with VO^{2+} and VO_2^+ ions, while the negative side refers to the negative electrode and tank with V^{2+} and V^{3+}.

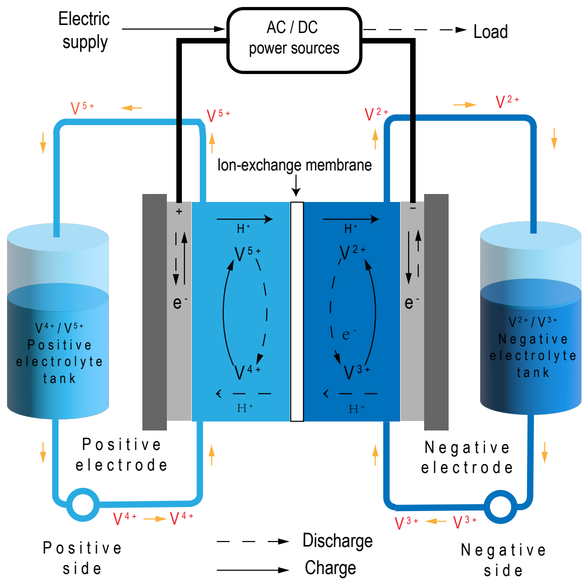


Figure 2: A schematic diagram of a typical VRFB system

The electrolytes are stored in the reservoirs, transferred through the pipes into the half-cells, and returned to the reservoirs for re-circulation [52]. Each half-cell comprises an electrode with a bipolar plate, the redox species react on the electrode, and the current flows through the bipolar plate. The two half-cells are separated by an ion-exchange membrane to conduct supporting vanadium ions in the electrolyte and to prevent the transfer of the redox-active vanadium ions to prevent electrolyte cross-contamination [53]. The battery stack has multiple cells in an array, and adjacent cells share a bipolar plate. The number of cells determines the rated power of the VRFB [2]. The overall cell reaction is given in (1), with the positive cell reaction and negative cell reaction in (2) and (3).

$$VO^{2+} + V^{3+} + H_2O \underset{\text{Discharge}}{\overset{\text{Charge}}{\rightleftharpoons}} VO_2^+ + V^{2+} + 2H^+, \quad E^0 = 1.26\ \text{V} \tag{1}$$

$$VO^{2+} + H_2O \underset{\text{Discharge}}{\overset{\text{Charge}}{\rightleftharpoons}} VO_2^+ + 2H^+ + e^-, \quad E_p^0 = 1.0\ \text{V} \tag{2}$$

$$V^{3+} + e^- \underset{\text{Discharge}}{\overset{\text{Charge}}{\rightleftharpoons}} V^{2+}, \quad E_n^0 = -0.26\ \text{V} \tag{3}$$

In Fig. 3, a description of the VRFB is adapted from [2] to illustrate the ion species behavior during charging and discharging process. During the charging process, V^{3+} and V^{4+} are converted to V^{5+} and V^{2+}. Thus, chemical energy is converted to stored energy in the battery. During the discharging process, the V^{5+} and V^{2+} are converted to V^{3+} and V^{4+}, where the chemical energy converts to electrical energy through current flow (see Fig. 2). The function of the membrane facilitates the diffusion of H^+ ions between the two half-cells while preventing the cross-mixing of the electrolyte stored in positive and negative half-cell [54].

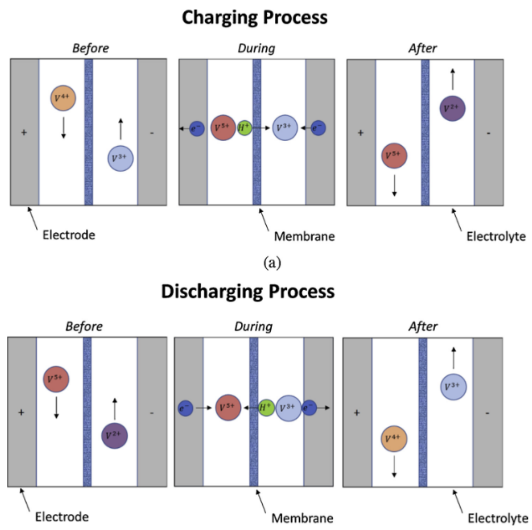


Figure 3: (a) Charging and (b) discharging process description of VRFB adapted from [2]

Different types of advanced VRFB membranes have been evaluated in laboratory tests [20, 21, 22, 23, 24, 25]. These are still expensive and may not be suitable for commercial applications. Several commercial membrane technologies are also evaluated in [26, 27]. Some of these have low permeability to the vanadium ions, which aggravates the vanadium ion diffusion [50]. This will lead to self-discharge reactions, significantly impacting the usable capacity. In this phenomenon, the vanadium ions are consumed without releasing electrons. This capacity loss associated with ion diffusion and side reactions is one type of internal loss caused by chemical reactions.

Overall, battery losses will lead to efficiency reduction, necessitating the study of losses and the development of appropriate loss models for VRFBs, particularly for optimisation and

Table 1: VRFB losses and influencing factors

Losses	Definition	Influencing factors	Reference
Pump system loss	The energy losses of the pump system operation	Flow rate, pump design, pump efficiency, converter efficiency	[55]
Cooling system loss	The energy losses of the cooling system. (Note: Some of the VRFB systems have a cooling system to avoid overheating)	Electrolyte temperature, ambient temperature, VRFB system design, battery housing design	
Ohmic loss	Power losses due to the transfer of electrons in the electric circuit carbon felts and bipolar plates and the movement of ions through the electrolyte and membrane.	Internal resistance, current density, electron and ion transportation resistance	[56, 57]
Crossover loss	Capacity losses due to the diffusion of vanadium ions causing self-discharge reactions in the VRFB system.	Membrane permeability of vanadium ions	[50]
Mass transport loss	Vanadium ion concentration loss due to the mass transport of the active species.	Low electrolyte velocity, low vanadium concentration in the solvent	[58]
Activation loss	The ratio of total discharge output power to total input power stored in VRFB.	Kinetics of the vanadium redox reactions	[57, 59]
Shunt current loss	The conductivity of the electrolyte and non-zero electrical field potential gradient will cause shunt current [60].	Conductivity of the electrolyte, number of cells, the shape of channel and pipes, internal resistances	[60, 61, 62]
Hydraulic loss (pressure drop)	The pressure drop in the hydraulic system mainly including friction loss in the pipe, congestion loss and other pressure drops in electrodes. (Note: The pressure drop studies normally help researchers to model the pump loss)	Shape of channel, pipes and manifolds	[55]

operation algorithms. Main VRFB losses are summarised in Table 1 by mentioning the associated influencing factors. The VRFBs have several internal losses similar to any other battery technology. Despite solid-state battery technologies, VRFBs suffer from external losses caused by the power-consuming components in the system to support their operation. Other sources of losses in VRFBs are caused by inadequate battery management command from BMS, electrolyte temperature rise, and cooling system operation. The main performance metrics of VRFB, their definitions and derivations are summarised in Table 2. They are the key indicators for the analysis of the efficiency and capacity performance of a VRFB system. In addition, several important attributes and parameters are listed in Table 3 that are the critical system states and parameters for battery modelling and management.

2.2. Main features of VRFB

The main features of VRFB are different from those of other solid-state batteries, e.g., lithium-ion and lead-acid batteries, due to their unique structure and operation principles. Compared to other flow batteries, e.g. zinc-bromine, the same metal ions are employed in the electrolyte to prevent cross-contamination issues, which results in a long lifespan [63]. The advantages of VRFB batteries are listed below:

1. Long life-cycle up to 20-30 years [51].
2. Flexibility in regulating the output power by increasing the size of electrodes or using more active vanadium species [66].
3. Unlimited capacity associated with the volume of the electrolyte.
4. High efficiency (up to 90% in laboratory scale, normally 70%-90% in actual operation) [67].
5. No cross contamination problems (accidental mixing of both electrolytes) compared to other flow batteries due to the same vanadium ions in different electrolytes, thus ideally no degradation [68].
6. Electrolyte is recyclable.
7. Low manufacturing cost and maintenance cost [2].

The downside of VRFBs can be summarised as follows:

- Low energy density.
- An efficient thermal management system is required to prevent thermal precipitation of vanadium species.
- Hydrogen evolution generated at the electrode is harmful to the VRFB system and overall efficiency.
- Poor fast response performance than lithium-ion batteries, with limited capability to handle sudden peak demand.
- Highly oxidising nature of V^{5+} can damage the membranes and positive electrode terminal [68].

To highlight the technical advantages and downside of VRFB system compared with other mainstream battery storage technologies, a detailed comparison result of five mainstream battery technologies is given in Table 4 with nine important technical indexes.

2.3. VRFB Applications

The first practical VRFB (a 5 kW/12 kWh unit) was built by the University of New South Wales (UNSW) and installed in a household with rooftop solar photovoltaic (PV) [14]. After the successful field trial, many companies started commercialising the technology for various applications related to power systems. At the same time, more research and development (R&D) money advancing RES technology and technical improvements in manufacturing and mass production significantly decreased

Table 2: Performance metrics of VRFB, definition and formulation

Performance metrics	Definition	Derivation
Battery efficiency	The ratio of the total discharged energy to the total charged energy.	$$\mathrm{BE} = \frac{\int V_{dis}(t) I_{dis}(t) dt}{\int V_{ch}(t) I_{ch}(t) dt} \quad (4)$$
Voltage efficiency	The ratio of average discharge voltage to average charge voltage.	$$\mathrm{VE} = \frac{\int V_{dis}(t) dt_{ch}}{\int V_{ch}(t) dt_{dis}} \quad (5)$$
Coulomb efficiency	The ratio of discharge capacity to charge capacity in coulomb counting method.	$$\mathrm{CE} = \frac{\int I_{dis}(t) dt}{\int I_{ch}(t) dt} \quad (6)$$
System efficiency	The ratio of total output power during discharge to the total input power during the charging period.	$$\mathrm{SE} = \frac{\int_0^{t_{dis}} (P_{dis} - P_{loss})\, dt}{\int_0^{t_{ch}} (P_{ch} + P_{loss})\, dt} \quad (7)$$
State of Health (SOH)	The ratio of the maximum battery charge to the rated capacity.	$$\mathrm{SOH} = \frac{Q_{max}}{Q_{rated}} \quad (8)$$

Table 3: Attributes and parameters of VRFB

Attributes/parameter	Definition
Cell voltage	The electromotive force of a single VRFB cell at 50% SOC (normally 1.26V).
Stack voltage	The electromotive force of the VRFB at 50% SOC.
Open circuit voltage (OCV)	The cell voltage without circuit connection.
Current density	Current applied per membrane area.
Ideal capacity	Ideal capacity stored in a certain volume of electrolyte.
State of Charge (SOC)	Charge level relative to its capacity.
Flow rate	The volume of fluid which passes per unit time from tanks to stack and vice versa.
Power density	The ratio of the total power capacity to volume.
Energy density	The ratio of the total energy to the volume.
Minimum and maximum stack voltage/power/current	The minimum and maximum stack voltage /power/current that are allowed during the operation.

the cost of renewable generation. For example, the global on-shore wind levelised cost of energy (LCOE) had a year-on-year drop of 13%, while the global off-shore wind LCOE had a year-on-year drop of 9%. At the same time, a 7% year-on-year drop in the utility-scale solar PV LCOE has been achieved [69]. The RES cost reduction and wider application have increased the need for VRFB as a large-scale ESS for smoothing and peak shaving, MG application, and RES capacity firming, among others. In the following subsections, different applications of VRFBs are reviewed, and real-world examples are given.

*2.3.1. **Energy storage system in MG***

In MGs (particularly stand-alone ones), ESSs are vital components to support the energy generation from RES, increase the reliability of operation and improve grid utilisation at users' end [70]. Various energy storage technologies, including but not limited to thermal energy storage (TES), compressed air energy storage (CAES), flywheel energy storage (FES), small-scale pumped hydroelectric energy storage (PHES), capacitor/super-capacitor (SC) energy storage, sodium-sulfur (NaS) battery, fuel cell (FC), lead-acid battery, lithium-ion battery, redox flow battery (RFB), etc [2] [70] have been suggested for MG applications in particular. A detailed comparison in [70] shows the advantages and disadvantages of major ESS for MG applications. Among these ESSs, RFBs are considered the most promising option for large-scale energy storage in energy shifting, frequency regulation, peak load matching, and peak shaving [70]. Among different RFBs, the VRFBs have technical advantages such as a stable technical system with fast chemical reactions, low gas evolution, higher efficiency, low capacity degradation and low maintenance cost for MG applications. A detailed performance comparison was presented in [70] to demonstrate the technical superiority of VRFBs among mainstream RFBs.

Several MG trials in Japan, China, and the USA [70] used VRFBs for variable RES storage, RES power smoothing, peak shaving, and backup power [70]. The most common use of VRFB in MG is for RES storage and power smoothing. Qiu et al. studied a 5 kW/20 kWh VRFB with a 6 kW PV array as a standalone MG system at Fort Leonard Wood, Missouri, USA in [10]. A model of the VRFB was used to validate the performance of the VRFB operation in the field. One of the main challenges in deploying the VRFB in MG is the indepen-

Table 4: Comparison of VRFB and other mainstream energy storage batteries [63, 64, 65]

	VRFB	Lithium-ion	Lead-acid	Nickel-cadmium	Sodium-sulfur
Lifespan	20-30 years	5-15 years	2-15 years	10-20 years	10-15 years
Lifecycle times	10,000-16,000	100-10,000	250-2000	1000-5000	2500-40,000
Power and capacity	Unlinked	Linked	Linked	Linked	Linked
Depth of Discharge	100%	100%	80%	80%	100%
Energy density	18-45 kWh/m^3	95-500 kWh/m^3	25-90 kWh/m^3	15-150 kWh/m^3	150-300 kWh/m^3
Efficiency	75-90%	75-97%	63-90%	60-90%	75-90%
Working temperature	5-45°C	20-65°C	18-45°C	-40-50°C	330-350°C
Self-discharge rate	0% per day	0.1-0.3% per day	0.1-0.3% per day	0.2-0.6% per day	0% per day
Energy cost	130-850€/kWh	500-2100€/kWh	40-170€/kWh	680-1300€/kWh	250-420€/kWh

dent power and energy ratings inherent in VRFB systems. It requires an in-depth analysis of the required output power and storage capacity to achieve the best scheduling capability, and minimum cost in a MG [71]. Nguyen et al. proposed a dynamic programming (DP) algorithm to solve the optimal scheduling problem and determine the optimal power and energy ratings for the isolated and grid-connected MGs [71], which handle the constraints of VRFBs. In [71], a VRFB has been used to smooth power and maintain the stability of the MGs. Ontiveros et al. introduced a power conditioning system (PCS) to compensate for wind energy fluctuations by incorporating a VRFB system with a wind turbine in a MG [72]. In [73], Safipour et al. studied the optimal planning of a VRFB in a MG with wind power generation to improve the operational performance indicators, which also showed the benefits of high flexibility and low operation, maintenance and replacement cost of the VRFB unit. Another application of VRFB is reported in [74] for a MG with a wind turbine, which studied the optimal allocation of the VRFB in the system (an active distribution network) considering the dynamic efficiency and lifespan of the VRFB. The paper formulated a comprehensive model of the wind turbine generator, load, environmental factors and VRFB dynamic to optimise the energy flow in MG [74].

In [9], Merei et al. introduced an off-grid hybrid PV-wind-diesel system utilising a lithium-ion, lead-acid, VRFB or a hybrid battery system, which helps to achieve the lowest cost and pollution in operation. This hybrid MG is modelled and tested in MATLAB/Simulink using real solar irradiation, wind speed and ambient temperature data from Aachen, Germany, with 10-minute interval data for 10 years [9]. This study showed that the VRFB is the most cost-effective and technically-efficient ESS for that particular stand-alone MG. In [75], first, a solar PV-wind-biogas-VRFB MG is optimally designed. Then, an intelligent scheduling and controller system is developed for the MG daily operation [75]. In [76], the VRFB is developed in a transport MG to utilise the recovered energy from the train and achieve peak shaving. In [77], a 5kW/20kWh VRFB was installed on a portable and expandable MG for off-grid energy systems. They have shown that VRFB could be a promising solution for a small-scale energy storage system. These two studies expanded the breadth of the VRFB applications in both large-scale and portable MG.

2.3.2. ***Residential and community storage***

Residential and community level ESSs are more popular in the industry. They can facilitate electrification, self-sufficiency, carbon emission reduction, grid upgrade postponement, energy democracy, resiliency and reliability, and reduction in electricity costs at the residential or community levels [78, 79, 80]. Although different battery technologies (e.g., lithium-ion and lead-acid batteries) have been used in autonomous residential and community grids in the last several decades, the VRFBs are newly added to the market in this area. VSUN Energy, Australian Vanadium Limited, VoltStorage, and several other companies are developing (or have already launched) commercial VRFB products for home energy storage [81, 82, 83]. Only a few researchers have studied the prospects of VRFBs for residential and community applications. In [84], with a focus on an emerging organic photovoltaics (OPV) system, the authors claimed that the VRFB-OPV hybrid system could be one of the solutions in a residential application. Terlouw et al. presented a multi-objective optimisation of energy arbitrage with different battery types in a community ESS [85]. The aim of this optimisation was to minimise the operational cost and CO_2 emissions. The result of this study illustrates a profitable operation for a community-scale VRFB ESS [85].

2.3.3. ***Renewable power plants***

In 2020, global renewable energy usage increased by 3%, and the global electricity generated from RESs increased by 7% in the same year [86]. However, their dependence on weather conditions complicates power system operation. One solution is to use short-term storage to smooth/firm their output power and increase their capacity factor. Extensive field studies have been conducted worldwide to evaluate the application of VRFB in RES power smoothing. For example, a 4MW/6MWh VRFB was installed at a wind farm in Hokkaido, Japan, to smooth the fluctuations in generation and increase the reliability of the wind farm [14]. 1 MW/5 MWh and 400 kW/500 kWh VRFBs are installed in Japan and Indonesia, respectively, in solar farms to balance the fluctuations [14]. See [14] for more VRFB applications in REs plant smoothing and short-term storage. These trials proved the advantages of VRFB in renewable power plants, in addition to load-levelling, peak shaving, and power arbitrage [15].

2.4. *Current challenges in VRFB applications*

The VRFB has unique features, as explained in Section 2.2, that make the technology a reliable, economical, and environmentally friendly solution for MG, residential and community storage and renewable power. Nevertheless, the technical challenges of the VRFB will have a non-negligible impact on its performance; thus, an efficient BMS with power and energy management functionality is vital for the efficiency, stability and reliability of the entire energy system. Moreover, thermal management and charging control are two core aspects of the VRFB system to prevent the electrolyte temperature from exceeding the safe limit. Therefore, a comprehensive thermal battery model is necessary for the electrolyte temperature estimation in different components, together with a state of charge (SOC) estimation function to prevent batteries from being overcharged and over-discharged. Furthermore, the pump loss and shunt current loss are the two factors that limit the round-trip efficiency [87].

Another reason to have proper BMS is to manage and protect the battery system under varying ambient and operational environments. This includes monitoring the battery state (mainly thermal and SOC), data processing, data storage and communication, intelligent charging/discharging control, maintenance reminders, fault alarms and pump control for system efficiency maximisation, etc. Generally, battery models are used within a BMS to ensure safe operation, optimisation and data processing, which help improve the battery system's performance under various physical constraints. Additionally, an effective EMS is important in the VRFB-based power system applications to reduce the load fluctuations, increase the economic benefit, balance the supply and load demand, enhance dynamic frequency response, and other functions to improve the efficiency and economic performance [44, 11, 88].

Considering these aspects will enable VRFBs to be applied more widely. Therefore, in the rest of the paper, we describe the state-of-the-art VRFB modelling techniques, BMS and EMS, summarise the caveats in current systems, and suggest future research direction.

3. VRFB modelling techniques

3.1. ***Overview***

Appropriate battery models are a cost-effective and practical way to estimate and predict fundamental battery parameters such as SOC, stack voltage, open circuit voltage (OCV), chemical characteristics and thermal behaviour. The predictive ability of the battery models is practical for battery design and optimisation, aiming to increase the battery/system efficiency, malfunction diagnosis and prognosis and lifespan extension.

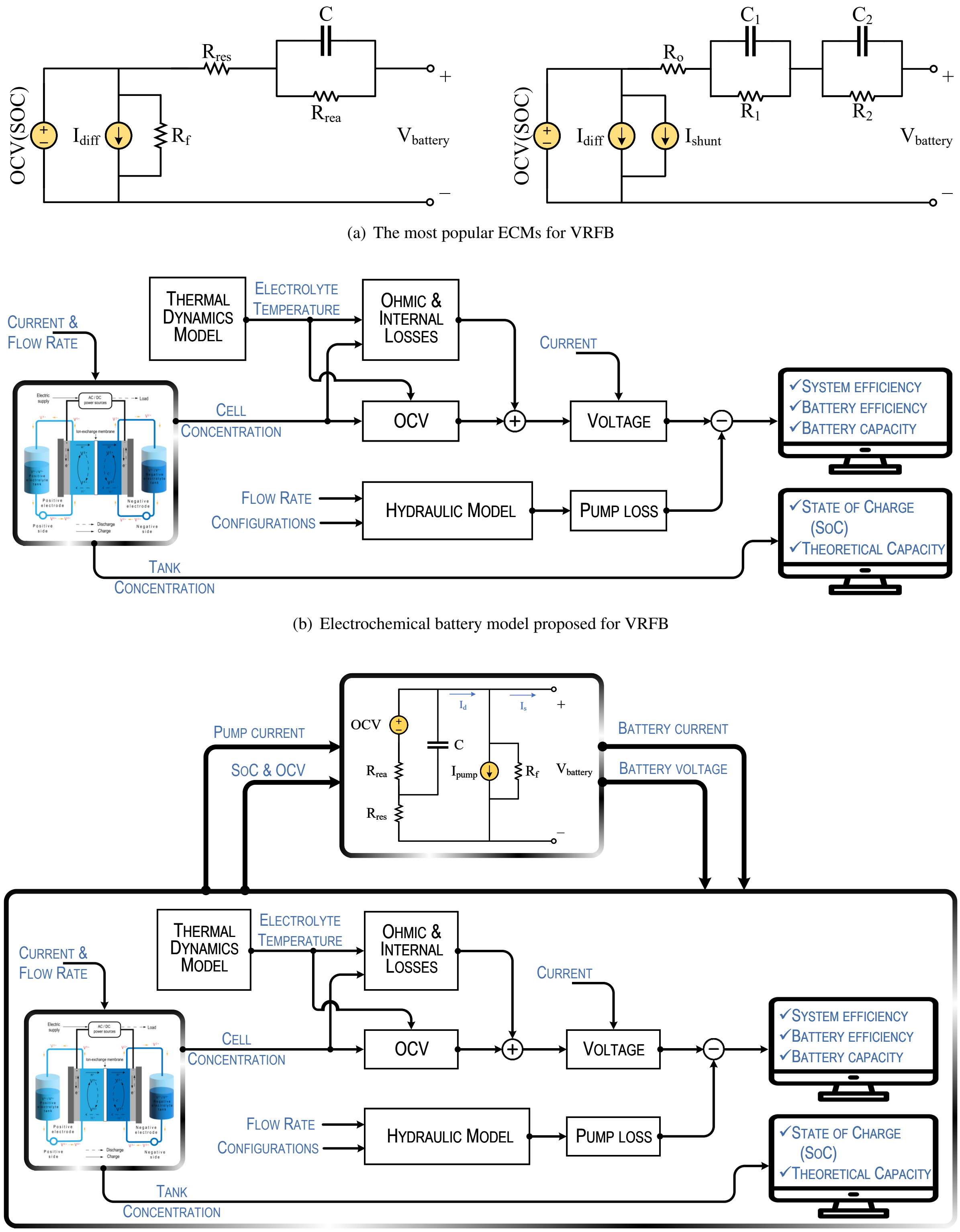
Specifically, the VRFB models are the building blocks for battery state monitoring and advanced automated control during charge-discharge operation. The VRFB models generally address two issues. The first is the unobservability of some system states, such as OCV, active species level, capacity, etc., where the battery models are employed for state estimation. Moreover, some other system states, including SOC and state of health (SOH) are difficult to accurately be estimated via simple Coulomb counting methods. The joint application of battery models with battery estimation technologies is an efficient way to gain more accurate results, which have been studied and proposed for various types of batteries. Besides, these proposed VRFB models enable researchers to understand the principle and behaviour of battery systems. Through developing different VRFB models, researchers found an efficient approach to secure the long-term stability and efficiency of VRFB systems linked with hydraulic system pressure drop, flow rate optimisation, charge current optimisation, temperature management, and electrolyte rebalancing.

VRFB models can generally be categorised into equivalent circuit models (ECMs), electrochemical models (EMs), hybrid, and artificial intelligence (AI)-based (data-driven) models. The ECMs were initially proposed for other types of batteries (e.g., lead-acid and lithium-ion) modelling and has been adapted to the VRFB. These models use a circuit model of different orders and allow for simulating the physical mechanisms instead of the electrochemical mechanisms; hence, it is simpler to form the state-space representation. The EMs were established based on the mass balance equation, energy conservation law and ion diffusion to simulate mechanisms of the chemical reactions inside the battery cells. The hybrid model is a relatively new generation of battery models that combines the merits of the two models mentioned above and is an efficient way for battery analysis and state estimation. The AI-based battery models are applied to improve the estimation accuracy of a VRFB system that is more adaptive to solving the constraints in system uncertainties. In the following subsections, the four modelling categories are discussed in detail.

Battery models employ different methodologies to describe dynamic behaviour. For a typical battery, the chemical characteristics are studied to describe its dynamic properties, including internal chemical reactions, thermal dynamics, degradation, stability and capacity. Moreover, studying physical characteristics contributes to modelling the battery output, including voltage variation, efficiency and charge-discharge behaviour. The joint study of electrochemical characteristic form a comprehensive battery model to accurately predict the battery characteristics. Several types of VRFB models have been developed by researchers from different disciplines and applied in various applications. These battery models differ in input parameters, outputs, accuracy, simulation tools and response time. Three types of VRFB models, most commonly used in research, are the ECM, EM, and hybrid model [5]. The AI-based battery models are a recent development proposed to enhance the state estimation accuracy. These proposed VRFB models are available for different application scenarios containing different functions and availability.

3.1.1. ***Equivalent circuit models (ECM)***

The ECM is developed to describe the battery's external/dynamic electrical characteristics via the use of fundamental electrical components, including resistors, capacitors, and a voltage source to form a circuit network. Originally, the ECMs have been developed for older battery technologies,



(a) The most popular ECMs for VRFB

(b) Electrochemical battery model proposed for VRFB

(c) Hybrid model proposed for VRFB

Figure 4: VRFB models implementation process

e.g., lithium-ion and lead-acid. In recent years, various ECMs have been developed and studied by researchers for VRFB in [89, 90, 91, 92, 93, 94, 95, 96, 97].

In particular, a simple ECM, also known as first-order resistance-capacitance (RC) ECM, is proposed in [92], which considers the internal self-discharge and pump losses. Relevant research related to VRFB has been carried out based on this simple ECM in [90, 91, 92, 97, 98] to solve control and state estimation problems in different applications. In this simple model, the thermodynamic equilibrium potential of the battery is presented by a voltage source, with an electrode capacitance and loss resistances to simulate the electrical characteristics of the entire VRFB system. In [97], a detailed design scheme of this simple ECM is introduced, which divides the battery model into three subsystems: stack voltage estimator, SOC estimator and pump model. This demonstrated a more detailed implementation approach to consider the influence of the pump loss as a shunt resistance in the simple ECM. Moreover, an online parameter and SOC estimation study is carried out in [98] based on this simple ECM. This study showed the effectiveness of this ECM in advanced parameter and state estimation studies. Same as the first-order RC-ECM, second-order RC-ECMs are commonly used in the literature due to their simple structure with higher accuracy and adaptability for different parameter identification methods [99]. In these models, again, a voltage source represents the thermodynamic equilibrium potential of the battery with two additional RC networks describing its dynamic characteristics. These two VRFB models are broadly combined with different parameter/state estimation techniques (recursive least square method family, Kalman filter family, etc.).

The n^{th}-order ECM mentioned above requires online estimation techniques to enhance the estimation accuracy due to changes in the battery cell's internal chemical state, significantly impacting its thermal dynamics and capacity degradation. In [93, 94, 96], online identified ECMs based on first-order or second-order RC-ECM are presented with online updating of the estimated value of parameters, which results in enhanced state estimation accuracy. To consider the dynamic factors arising from chemical reactions, Xiong et al. proposed a thermal-dependent ECM with a thermal prediction module to simulate the impact of thermal dynamics on the OCV of the VRFB [100]. In [101, 102], Xiong et al. improved the thermal-dependent model with a capacity fading factor to simulate battery degradation caused by the self-discharge reactions and other internal losses. All of these studies improved ECMs by considering the dynamic characteristics of the VRFB system with enhanced efficiency via the use of adaptive estimation techniques. Moreover, Han et al. recognised the significance of self-discharge reactions in the VRFB models and proposed an improved first-order ECM in [95], which contains a self-discharge resistor connected in parallel with the RC ladder to simulate the self-discharge losses during battery operation [95]. This improved model has the potential to estimate the capacity reduction during charge-discharge cycles and assess the capacity reduction rate under different SOC levels [95].

With an in-depth understanding of the VRFB principles, comprehensive ECMs have been developed to reflect the ECM's electrochemical, hydraulic and thermal dynamics. Although several vital factors, including thermal dynamic, pump loss and capacity fading of the VRFB system, have been considered in [100, 101, 102, 95], these ECMs are formulated based on the mass balance equation, energy conservation law, Nernst equation, Bernoulli equation and conventional ECMs. In [103], Zhang et al. proposed a comprehensive ECM that assessed the shunt current, effect of ion diffusion, and hydraulic model based on a second-order ECM. Also, a first-order ECM with a parameter identification process is presented in this study to validate the applicability of the proposed ECM. A similar study was carried out in [104] considering the effect of the pump and shunt current losses in the proposed accurate ECM. These studies illustrated an approach to linking the electrochemical equations into the circuit topologies to establish a more comprehensive ECM for single-cell and multi-cell VRFBs. In [105], an ECM is proposed for the entire VRFB stack by connecting 40 first-order ECMs for a single cell in series. It is the first time that a dynamic ECM of a whole stack has been validated in an IS-VRFB system, which is significant for the future development of online SOH estimation for VRFBs.

In conclusion, many researchers studied ECMs as the primary modelling technique based on the associated equations between current, voltage and SOC, with additional consideration of VRFB characteristics, including its thermal dynamic and hydraulic system scheme. However, two major issues affect the accuracy of these models. First, the parameters estimated using offline identification methods may not reflect the true battery dynamic under a varying current. Although advanced estimation algorithms, e.g., extended Kalman filter (EKF), potentially can handle the constraints within an online parameter identification process, the estimation accuracy is restricted by the initial setting of these parameters. Second, the OCV in these ECMs is approximated by the SOC-OCV polynomial function. Inaccurate SOC estimation will reduce the accuracy in OCV estimation and thus decrease the accuracy in parameter estimation. Nevertheless, the ECMs are highly applicable to estimate the electrical properties of VRFBs, but ignoring fundamental chemical states (e.g., ion concentration and electrolyte temperature) in these models jeopardises the accuracy of SOC and capacity estimation. A detailed summary of the developed ECMs mentioned above has been presented in Table 5.

3.1.2. Electrochemical models (EM)

An EM is formulated based on the internal chemical reactions inside a battery cell, where understanding the state variations of the vanadium ions is fundamental to modelling its operating mechanism. Combining the energy conservation equation, Nernst equation, mass balance equation and Bernoulli equation, a numerical ordinary differential equation (ODE) can be established to study the vanadium ion concentration variations with flow rate, electrical characteristics, hydraulic system design and electrolyte temperature. The EM has the ability to simulate VRFB operation with current and flow rate as input parameters, aiming to estimate the active species concentrations and hence the SOC, stack voltage and other performance parameters. Moreover, EMs play a critical role in battery structure design and optimisation using simulation studies to gauge the impact of battery configurations, electrolyte and membrane material on its performance.

Mathematical models have been developed and assessed in [106, 107, 108, 109, 110, 111, 112] to predict the performance of the VRFBs. However, the proposed two-dimensional and three-dimensional models in the literature are useful in VRFB design but not so helpful in control and operation scheduling/management. Also, these models neglect the capacity loss caused by the ion diffusion [50]. Tang et al. in [50] proposed a dynamic VRFB model considering the effect of ion diffusion and side reactions to study the capacity loss in VRFBs. However, the proposed dynamic model did not consider the thermal dynamics of the VRFB, which may lead to thermal precipitation in the electrolyte. A thermal model of battery configuration and self-discharge reactions in VRFB was proposed in [113] based on the dynamic model from [50] to avoid the thermal precipitation by estimating the electrolyte temperature in the tanks, pipes and stack during the charge-discharge cycle. The thermal dynamic model is formulated based on energy balance equations and mass balance equations to form a comprehensive battery model for system state estimation, control and optimisation purposes [113].

Nevertheless, these models were developed assuming that the VRFB cells act as continuous stir tank reactors (CSTR) in which the vanadium ions are distributed uniformly throughout the cells [114]. This assumption may be appropriate in a laboratory scale VRFB, but does not hold true for commercial systems with larger dimensions [114]. In [114], the authors assumed the VRFB cell acts as a plug flow reactor (PFR) by extending the dynamic model to a multi-layer model to consider the effect of vanadium ion variations between the inlet and outlet of the cell [114]. The proposed multi-layer model in [114] shows the discrepancy in cell voltage and concentration level between different layers, which suggests studying the effect of concentration imbalances in the battery stack. A detailed summary of the developed EMs mentioned above has been presented in Table 6.

3.1.3. *Hybrid models*

The EMs and ECMs are the most commonly used models to simulate VRFB operation. While the conventional ECMs neglect the chemical characteristics and hydraulic design of the VRFB system, the EMs are highly nonlinear, complicating SOC observation and adaptive state estimation. Considering the strengths and pitfalls of these models, a multi-physics hybrid model is proposed in [5] based on electrochemical properties and principles and the mechanism of battery operation. The proposed hybrid model integrates ECM and EM, reflects the internal chemical dynamics via the electrochemical battery model, and simulates the electrical characteristics of the ECM [5]. Implementing the hydraulic mechanism, thermal mechanics and other factors inside the VRFB system forms a comprehensive hybrid battery model that overcomes the limitations of a single model, e.g., insufficient parameter estimation and inaccurate system state estimation. However, the hybrid models have their limitations, such as being less appealing in practical applications and even in simulation studies due to their computational complexity [5].

3.1.4. *AI-based battery models*

Recent development in AI and data-driven modelling has reached the VRFB modelling domain to solve complex problems in battery modelling and state estimation. For example, neural networks (NNs), an AI-based algorithm with a strong nonlinear fitting ability, have been used to fit the dynamics of a battery system without considering its physical structure and operational principles. A relationship was found between the inputs and outputs during the training process using training data.

In [115], field analysis and NN are used to model a VRFB system based on a reduced-order circuit model. The proposed adaptive NN (ANN) aims to simulate the operation of the heating, ventilation and air conditioning (HVAC) system and ambient environment. This study introduced an ANN method that considers ambient variations to form a detailed model for an entire VRFB system. An enhanced physics-constrained deep neural network (ePCDNN) approach is introduced in [116] to enhance the performance of a physics-based zero-dimensional VRFB model with extreme voltage response [116]. The results show the proposed ePCNDD framework can achieve high accuracy in voltage response, which can also be used in battery system design and optimisation.

3.2. *Model evaluation and validation*

All battery models need to be evaluated and validated properly by experimental data. The evaluation of battery models guarantees that the core functions of the proposed battery model are achieved, e.g., type of battery model, input and output variables, model complexity and computational burden, and model accuracy.

In general, battery model applicability is evaluated by analysing the objectives and characteristics of the application, using the minimum number of input parameters and the lowest computational requirements to maximise the accuracy of the battery performance prediction. Also, validation of a battery model aims to investigate the technical performance by evaluating the simulation results estimated by the model against the experimental data. This could be the long-term and short-term capacity degradation, voltage and capacity under different flow rates and currents, electrolyte temperature and thermal dynamics, charge voltage and current under different input power and pump loss and hydraulic pressure drop during various operations.

4. Battery management system (BMS)

4.1. *Overview and functionalities*

A well-designed BMS is responsible for properly managing VRFB's operation during charging-discharging cycles and system state monitoring for safety issues and performance enhancements. The definition of the BMS varies in different applications and typically refers to a developed management scheme to locally monitor, control, and optimise the efficiency of an individual or multiple battery modules and minimise the degradation level [125]. For an independent VRFB system formed by the battery units and converters, a BMS is an integral part of the system and must be developed within the whole infrastructure [99]. From the power systems perspective, a BMS is customarily integrated to manage the battery operation and works in collaboration with an energy management system (EMS) or power

Table 5: A summary of the major ECMs for VRFB in the literature

ECM	Descriptions	Reference
Simple ECM considers internal losses (same as first-order RC-ECM)	A simple model considers the internal losses and physical properties of the VRFB. However, the parameters of the proposed ECM have limited accuracy because electrical parameters are based on the estimated values reported in [90, 91, 92, 97]. It also neglects chemical and thermal dynamics effect on the system. Adaptive estimation techniques (EKF, recursive least square-EKF (RLS), particle filter (PF) etc.) are necessary to have more accurate parameter identification results under these simple ECMs, as shown in [98].	[90, 91, 92, 97, 98]
n^{th}-order RC-ECM	An electrical circuit-based ECM model with a 2^{nd}-order RC ladder is proposed to consider the equilibrium cell voltage, ohmic resistance and other dynamic parameters. These general RC-ECMs also need adaptive estimation algorithms (e.g., EKF, RLS-EKF, PF etc.) to perform well in parameter identification,e.g., SOC and SOH estimation. These proposed estimation algorithms based on ECMs do not consider the battery's chemical characteristics. The OCV in these nth-order ECMs is simply obtained via a polynomial relationship between the OCV and SOC, which has limited accuracy without using enhanced SOC observation methods.	[93, 94, 96]
Thermal-dependent ECM	A thermal prediction module is proposed in the thermal-dependent ECM to additionally consider the impact of thermal dynamics on the VRFB system. However, the heat transfer parameters in the thermal prediction module are difficult to obtain in real VRFB systems, thus, decreasing the accuracy of the thermal dynamic estimation.	[100]
Thermal-dependent and capacity fading dynamic ECM	Thermal prediction module and a capacity fading factor is added to consider the impact of thermal dynamic and capacity degradation on the VRFBs. The problem of the thermal prediction module are the same as mentioned in the thermal-dependent ECM. Moreover, the capacity fading factor is formulated based on an EM or experimental results, which increases the complexity in practical applications.	[101, 102]
ECM considered self-discharge for SOC estimation	Self-discharge was taken into account in the ECM, using a resistor connected in parallel with the RC ladder to simulate the capacity fading based on the self-discharge test profile. The simulation results from this type of ECM have a better performance when the EKF-based method is applied to the terminal voltage and SOC estimation. However, the average SOC estimation error has not been discussed in the literature, and the parameter estimation process of the RC ladder is not demonstrated.	[95]
Precise dynamic ECM	An internal parameter extraction method is proposed based on a hybrid RC-ECM with shunt current and parasitic losses in this type of ECM to illustrate the parameter variations according to the flow rate, current and battery state. Besides, the hydraulic and thermal models are established to simulate the battery operation more accurately. The results show the proposed precise dynamic ECM has good accuracy in VRFB terminal voltage estimation and is applicable in RES system management. The internal parameter extraction method relies on the formulation of the terminal voltage, which is not adaptable in other applications with a varying flow rate and operational environment.	[98]
Comprehensive ECM	An ECM considering the shunt current, diffusion current and hydraulic model to establish a comprehensive model for VRFBs for power system analysis. The simulation results show a solid performance in voltage estimation, but the estimation error increases with the flow rate.	[104]
Dynamic multi-cell ECM	A dynamic ECM of the entire VRFB stack established by connecting 40 first-order ECMs in series. The proposed ECM is validated in an IS-VRFB system with an accurate parameter measurement.	[105]

management system (PMS) to handle the objectives set by the energy system's operators while optimising the performance considering the overall systems and grid connection [125].

While a BMS is equally important in VRFBs and solid-state batteries [41], only a limited number of papers have discussed the principle of a well-designed BMS for VRFB. Relevant studies on general BMS design and lithium-ion battery BMS design have been reviewed in [125, 99]. In [125], Gabbar et al. reviewed the development and industrial standards for solid-state batteries and introduced the topologies, components and software framework for a proper BMS design. Typically, a proper BMS design should have six fundamental functions, including monitoring, protection, charging and discharging management, communication, diagnosis and data management [125]. These are general guidelines for current battery technologies. Considering the unique structure and operation of VRFBs compared to solid-state batteries, however, additional functions are essential for the VRFB-BMS. Moreover, unlike conventional solid-state batteries, VRFBs suffer from electrolyte thermal precipitation, vanadium ion imbalance and hydrogen evolution which need to be considered for the overall system's safety and reliability. Therefore, a special BMS design is needed to handle the differences and constraints associated with VRFBs. Besides, it is vital to enhance the VRFB system efficiency and longevity by finding a proper flow rate [41]. The functionality requirements of VRFB-BMS are shown in Fig. 5 and are discussed in detail in the following subsections.

4.1.1. Monitoring

The primary task of a BMS is the monitoring of the most crucial system states affecting the performance and safe operation, including terminal voltage, current, cell voltage, electrolyte temperature, and SOC. These states are monitored by sensors or estimated using appropriate battery models to pre-

Table 6: A summary of EMs in the literature

EM	Descriptions	Reference
Dynamic modelling of the side reactions and ion diffusion	This dynamic model studies the internal losses of the VRFB caused by ion diffusion and side reactions.The proposed dynamic model neglects the thermal dynamics caused by the chemical reactions. Also, it models the internal chemical processes in the battery cell without integrating the entire VRFB system including pumps, pipes and tanks.	[50, 117, 118, 119]
Thermal modelling of battery configuration and self-discharge re-actions	A comprehensive VRFB system model was proposed to take the thermal dynamics into account to avoid thermal precipitation in the electrolyte solution and overheating. The proposed model neglects the non-homogeneous vanadium ion distribution caused by different electrode reaction rates.	[113, 37, 56, 120, 121]
Dynamic plug flow reactor model	A dynamic model for a single cell is proposed similar to the CSTR model in [113] with additional consideration of the concentration variation of vanadium ions. A single cell is divided into multiple layers in the vertical direction to examine the heterogeneity in the concentration of vanadium ions. The proposed model is established under the assumption of cell and electrolyte temperatures remaining constant at room temperature. Without considering thermal dynamics, this model is not applicable for electrolyte temperature management to avoid possible thermal precipitation in the electrolyte solution and prevent possible overheating of the cell components [114].	[114, 7, 122, 123, 124]

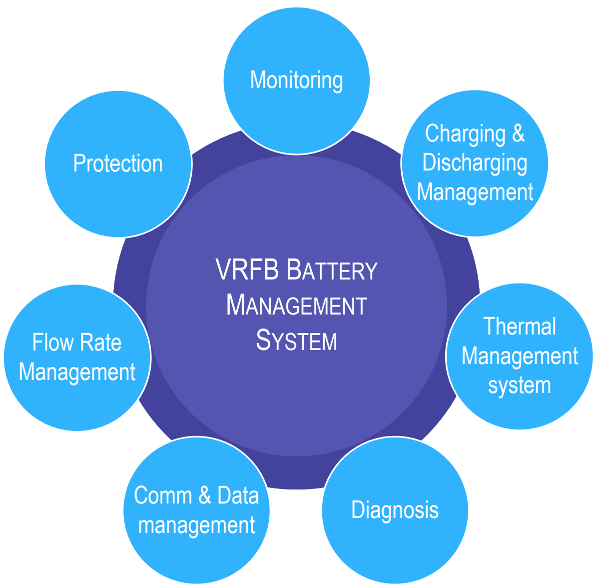


Figure 5: VRFB-BMS functionality requirements

vent hazardous situations, e.g., battery overcharge, over-current and overheating. Permanent damage to the membrane and battery cells may occur if they are exposed to these hazardous conditions. Since some of the system states, e.g., OCV, cannot be measured, or some other system states, e.g. SOC, electrolyte temperature, and active species concentrations, cannot be accurately measured or estimated, battery models and other adaptive estimation methodologies are inevitable to estimate the states accurately within the VRFB-BMS.

4.1.2. Thermal management system (TMS)

A TMS is necessary to reduce the risk of electrolyte thermal precipitation and hydrogen evolution, hence, preventing fire and explosion while minimising system losses [126]. According to [113, 127], too high or too low electrolyte temperatures may cause irreversible precipitation of vanadium species in the VRFB cell, which leads to energy losses [126]. The primary objective of the TMS is to control the electrolyte temperature within a safe limit, which ensures the safe, stable and reliable operation of the VRFB system [37].

4.1.3. Communication and data management

BMS operation depends on the parameters measured or estimated locally, such as voltage, current and ion concentration. Therefore, sensors, communication links and proper data management strategies are needed [128]. Also, building a database of historical values allows offline battery model development based on data-intensive approaches, such as artificial intelligence and machine learning techniques. Communication between different components is at the core of the entire system operation, which could be done using data sharing and access protocols. For instance, an EMS run by a third party should be able to access the battery SOC, temperature, current and voltage historical data.

4.1.4. Protection

The BMS prevents potential risks and protects people and equipment from battery-related incidents. The BMS protection could include operation mode detection, setting fault criteria, temperature management and overheating protection, fault detection, predicting system states, isolation fault detection, etc. [125]. Also, some local decision-making intelligence is needed for the BMS to protect the VRFB system by isolating the battery cells.

4.1.5. Charging and discharging management

The BMS must efficiently supervise a battery's charging and discharging operation to maximise its lifespan. The charging and discharging management regulates the SOC range and number of cycles and works harmoniously with the EMS by

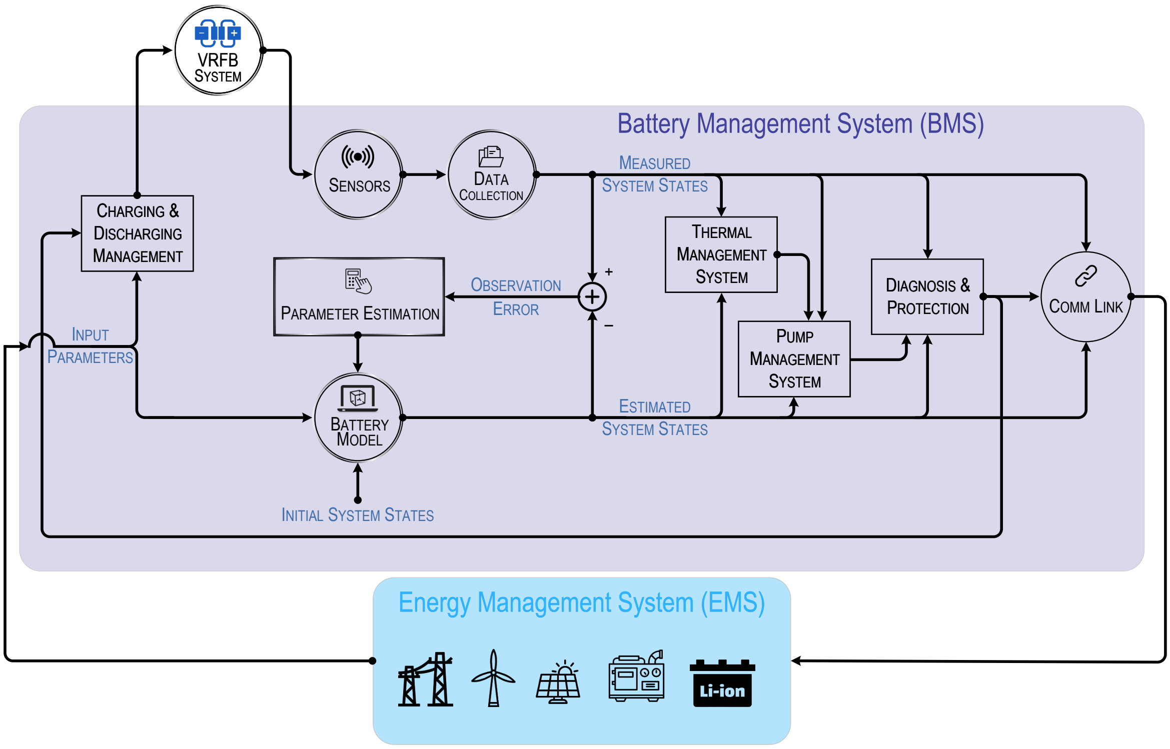


Figure 6: A hypothetical VRFB-BMS scheme with the proposed functionalities

controlling the input current, setting input/output power limitations, starting the pre-charge sequence, adopting different charging modes, etc.

4.1.6. Diagnosis and prognosis

The BMS monitors the sensor signals and the system states estimated by the battery models to detect potential faults and generate warning signals beforehand. The main faults could be voltage/current faults, inlet/electrolyte temperature faults, insulation faults, short-circuit faults, input/output power faults etc. Also, once a fault is diagnosed, the BMS produces a warning and responds based on the severity of the fault [39].

4.1.7. Flow rate management

The flow rate management is supervised by the BMS to adjust the flow rate by controlling the pump's speed. One of the main objectives is to control the dynamic flow rate to minimise internal and external losses resulting from concentration overpotential and pump loss under varying load power output conditions [129]. Besides, as another objective, flow rate management receives commands from the TMS to optimise the electrolyte flow rate to stabilise and manage the electrolyte temperature.

These functionalities form a comprehensive and efficient VRFB-BMS development scheme. Based on these functionalities, a hypothetical scheme is illustrated in Fig. 6 for VRFB-BMS to visualise the links between each functionality within the VRFB-BMS.

4.2. State-of-the-art BMS

As a newly developing battery technology, few publications have discussed the development of VRFB-BMS. To investigate an optimisation scheme for BMS operation focusing on the VRFB itself, Khaki and Das proposed a charging and flow rate management to realise fast charging and enhance the energy efficiency [130]. Their proposed VRFB-BMS is a multi-objective optimisation problem with different weighting factors assigned to fast and energy-efficient charging objectives. Nevertheless, their proposed BMS solely manages the charging process of VRFB considering input current and flow rate but neglects the electrolyte thermal dynamics, which may raise the electrolyte temperature and cause damage to the ion-exchange membrane. Evaluating the electrolyte temperature variations during the charge-discharge cycles, Bhattacharjee and Shaha developed an efficient thermal management system for VRFB in [37]. The proposed thermal management scheme can regulate the VRFB stack temperature within a safe range. Also, it adjusts the pump speed by a gain controller based on the estimation of the inlet stack temperature error, instant flow rate, and pump power by using a look-up table and stack power loss formulation [37]. The experimental laboratory test shows promising performance in achieving high overall efficiency while regulating the stack temperature within a safe range in charge-discharge cycles [37].

The aforementioned VRFB-BMSs explored a possible approach to manage the VRFB safely and aimed to maximise the overall efficiency with the lowest operational cost. However, the proposed schemes have not been validated on large-scale VRFBs integrated into a larger energy system. Furthermore, some of the main BMS functions have not been implemented in these BMS, e.g., communication and data management, monitoring, diagnosis and protection. In [41], Trovò et al. had a detailed description of a 9 kW/27 kWh industrial-scale (IS) VRFB-BMS, including the hardware design and software development [41]. The IS-VRFB-BMS uses a desktop computer with LabVIEW software and National Instruments compact data acquisition (DAQ) device [41]. A PMS is connected with the VRFB to provide electric power conditioning during the charge-discharge cycles through the bidirectional static converter [41]. The PMS is remotely managed and controlled by the BMS to regulate usage and quality of the input power [128]. This study addressed the gap by developing an advanced industrial-use VRFB-BMS, which has the potential for further research and practical development for industrial applications. Flexibility and expandability in operational decision-making are the two most crucial factors to achieving intelligent operation and future expansion in automatic control. Accordingly, the IS-VRFB-BMS should be modular, including signal management, surveillance system, software development and human-machine interface (HMI). A signal management module is devised to acquire the current, voltage and other system states from the sensors. These signals are transmitted to the BMS for further processing and action. A surveillance system (SS) is developed to protect the battery system against malfunctions and emergency conditions. A programmable logic controller (PLC) is dedicated to guaranteeing its reliability and coordinating with the BMS to ensure the safety of the VRFB system. The software development is the core of the IS-VRFB-BMS in [41] to designate the overall objectives and apply various optimisation algorithms under multiple scenarios. Moreover, an HMI is developed in [41] to allow users to review the states of the VRFB system and control the VRFB system accordingly. However, the proposed IS-VRFB-BMS only contains some of the essential functions to ensure the safe operation of the VRFB system but lacks an accurate adaptive SOC, SOH estimation method and flow rate optimisation. Combining newly developed state estimation and model-based nonlinear optimisation techniques would be challenging to improve its performance and longevity.

The state-of-the-art VRFB-BMS limitations and restrictions are listed below:

- The VRFB system is highly nonlinear, which increases the computational burden for advanced modelling and application of adaptive/predictive control algorithms.
- The chemical parameters (e.g., vanadium ion concentration) cannot be measured by sensors directly; hence complex models are needed for more accurate SOC and electrolyte temperature estimation.
- SOH estimation is important to ensure the long-term, cost-effective operation of VRFBs, similar to the studies on lithium-ion batteries [131]. However, there is only limited literature considering SOH estimation techniques in VRFBs [131, 132].
- Current ECMs developed for VRFB management need online parameter estimation. EMs have the potential to replace the ECMs models. However, their associated parameters (e.g., physical and chemical configurations for battery components) are difficult to obtain, leading to higher system state estimation errors.
- Solving a multi-objective optimisation is necessary for VRFB-BMS due to competing objectives, e.g., optimal flow rate and input current, which is complex and requires more computational resources to solve in real time.

The above restrictions lead to two major dilemmas for VRFB-BMS: 1) the current VRFB models are either nonlinear or require online parameter estimation, both of which need high computational power that may limit their application in industrial systems, 2) multi-objective optimisation algorithms and important system state estimation have not been validated in practical VRFB-BMS, which necessitates further feasibility studies for testing and verification.

4.3. Application developments of the VRFB-BMS

4.3.1. State estimation

Estimating SOC, SOH, active species levels, and other essential system states is the fundamental task of a VRFB-BMS. The SOC is recognised as the most crucial state in a battery system. An accurate SOC estimation prevents the over-charge or over-discharge of the battery, ensuring safe operation [121]. In previous BMS, coulomb counting and OCV methods (i.e., a relationship between OCV and SOC) are commonly used to estimate SOC. However, the method offers a limited current measurement accuracy due to neglecting the shunt current and other internal losses. Multiple SOC estimation algorithms have been studied for VRFBs, and the feasibility of these algorithms has been examined in the various electrical vehicle (EV) BMSs, and their performance has been validated.

Several model-based SOC estimation algorithms are proposed in the literature using Kalman filter (KF), EKF, unscented Kalman filter (UKF), particle filtering (PF) and sliding mode observers (SMOs). A general framework of the VRFB state estimation and parameter identification is shown in Fig. 7. In [93, 94, 121], the EKF was proposed to obtain more accurate SOC estimation. In [121], Xiong et al. applied the EKF in the thermal-dependent ECM for SOC estimation, which helped to improve the robustness of the EKF method. Qiu et al. in [98] introduced a gain factor in the EKF to establish an improved EKF (IEFK) method to estimate the SOC. The IEKF method achieves better accuracy, convergence speed and robustness when compared with EKF, and could be more applicable in industrial applications [98]. Khaki and Das proposed a new model in [96] for a hybrid model and applied the hybrid extended Kalman filter (HEFK) and PF methods. Their results show that these two methods adequately estimate the terminal voltage and SOC. Moreover, the terminal voltage estimated using the proposed hybrid HEKF-PF technique matched the experimental data in both constant current (CC) and constant voltage (CV) charging modes, and the HEKF algorithm

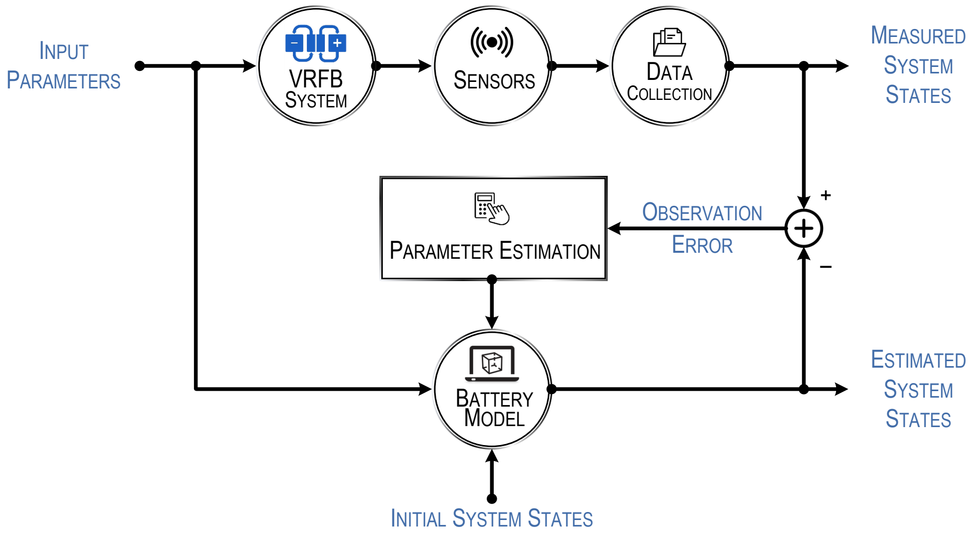


Figure 7: VRFB parameter identification and state estimation framework

has a better performance to adapt to various types of battery charging processes [133]. However, the proposed ECM-based hybrid HEKF-PF technique is computationally expensive for industrial applications. To reduce the complexity of SOC estimation, Khaki and Das [133] developed a fast and simplified ECM-based estimation algorithm to estimate the SOC and SOH with more practical significance jointly. Other advanced estimation algorithms are adopted from lithium-ion battery literature and applied to VRFBs. A reliable online SOC and capacity estimation is proposed in [134] using a multi-time scale KF-RLS method for SOC and capacity estimation individually. The proposed KF-RLS method requires lower computational resources, which makes it more practical in real-world applications.

Xiong et al. in [101] proposed an SMO for dynamic estimation of the SOC. The SMO method is expanded to estimate the SOC based on an EM by Clemente [135]. In [136, 137], two improved RLS methods, time-varying forgetting factor recursive least squares (TTF-RLS) and hybrid H_∞ filter RLS (HIF-RLS) are applied to the first- and second-order RC-ECM in an online parameter identification method. These two RLS-based methods perform accurately in tracking the variation of parameter dynamics, with a good performance in SOC and capacity estimation [136, 137].

Considering the unique merits of AI-based techniques mentioned in Section 3.1.4, the neural network (NN) is adopted to estimate the important state of the VRFB system as a reference value for the VRFB-BMS. In [138], a neural network-based method is studied to have a joint real-time SOC and capacity estimation. In this study, considering the degradation of the VRFB, a loss degree is classified into three levels via the probabilistic neural network (PNN). Using the backpropagation to train the model based on experimental data within each level, the capacity estimation result is obtained, and the SOC is calculated based on the online estimated capacity. This study is validated by experimental results, which show the applicability

Table 7: State-of-the-art state estimation techniques

Model	Parameters	Algorithm	Ref
ECM	SOC, electrolyte temperature	EKF	[121, 93, 94]
ECM	SOC	IEKF	[98]
ECM	SOC, terminal voltage	HEKF-PF	[96]
ECM	SOC, SOH	ECM-based	[133]
ECM	SOC, capacity	KF RLS	[134]
ECM	SOC	SMO	[101]
ECM	SOC, capacity	RTLS	[136, 137]
EM	SOC	SMO	[135]
EM	SOC, capacity	NN	[138]
EM	SOC	BPNN	[139]
EM	Cell voltage	PCDNN	[140]

of the NN in battery state estimation. Other relevant research is presented in [139] using the backpropagation for SOC estimation. A three-layer NN is proposed with the Bayesian regulation algorithm, and the result demonstrated the feasibility and accuracy of this method in online SOC estimation with a mean absolute error of less than 2% [139]. In [140], another NN-based cell voltage estimation study is carried out to train a deep neural network (DNN) with physical model constraints and battery sample data and a physics-constrained deep neural network (PCDNN) method. However, the proposed method does not estimate SOC or capacity; thus, it cannot be used in a modern BMS. Moreover, it is more applicable to utilise the PCDNN method in a battery model as an enhanced voltage capture method shown in [116]. In Table 7, a summary of the state-of-the-art state estimation techniques is given.

4.3.2. *Advanced optimisation*

Electrolyte flow rate and charge/discharge current are the two parameters with the most significant impacts on the battery performance, including electrolyte temperature, system efficiency and losses. These two parameters can be efficiently controlled to optimise the battery operation based on different objectives. Generally, these parameters significantly affect the concentration overpotential and pressure drop. Therefore, balancing these two factors to improve the system efficiency of VRFBs is an optimisation problem. From the previous literature, three common methods are presented and analysed in the following subsections.

Model-based optimisation. In the decision-making process, model-based optimisation is widely used to examine the influence of parameters on system performance. In [55], a concentration overpotential and pressure drop model is employed to study the trade-off between system efficiency and volumetric flow rate. It is shown that a high flow rate will reduce the concentration overpotential but cause a considerable increase in the pressure drop/pump power consumption [55]. An optimised variable flow rate with a flow factor of 7.5 was found to be the optimal solution for a 40-cell VRFB system at a given cut-off voltage limit compared with other flow factors and constant flow rate [55]. A similar study was carried out in [141], which considered the thermal-hydraulic behaviour of a VRFB system. Optimal flow rates under various charging currents are obtained from the thermal battery model based on several SOC values [141]. Compared with the results in [55], the study illustrated a significant impact on the electrolyte temperature caused by a high electrolyte flow rate, demonstrating the significance of the optimised flow rate to avoid electrolyte thermal precipitation. An innovative model-based flow rate optimisation method is proposed in [124], which reached the highest performance compared to conventional flow rate control methods (constant flow rate and variable flow rate).

The model-based optimisation methods in [124, 55, 121] presented efficient ways to study the impact of flow rate on the concentration overpotential and pressure drop. The main benefit of model-based optimisation is finding an approximate optimal flow rate within a specific condition, which contributes to developing 2D/3D look-up tables to improve the system's efficiency. Look-up tables are commonly used in industry to operate a system close to optimality with a limited number of parameters in the decision-making process. Nevertheless, the main restrictions of model-based optimisation methods are threefold: 1) model-based optimisation methods cannot be used as an online/dynamic operation, 2) the derived optimised flow rate is not the optimal flow rate throughout the entire operational process, 3) the model-based optimisation methods are not adaptive under a varying current or ambient temperature, which requires an iterative derivation of the optimised solution if the influencing factors or decision parameters alter, and 4) in a multi-objective optimisation problem with nonlinear terms and multiple decision factors, model-based methods may not be efficient because of computational complexity.

Model-based nonlinear dynamic optimisation. Considering the constraints in model-based optimisation results in a nonlinear optimisation problem, which necessitates model-based nonlinear dynamic optimisation algorithms to determine the optimal flow rate and charge/discharge current. The nonlinearities arise from the nonlinear battery models. The optimisation approaches depend on the predictive ability of the given electrochemical battery model. The optimisation problem is formulated mathematically to represent the objectives and technical constraints. For example, the charge/discharge current and flow rate are maintained within a boundary to avoid overheating and insufficient power output due to low flow rate and discharge current, and the SOC is kept within a safe range to prevent overcharge and discharge. This dynamic optimisation is an online optimisation that finds global optimal solutions and considers the physical constraints under pre-set objectives.

To investigate the feasibility of the model-based nonlinear dynamic optimisation method to realise the maximum energy harvest from RESs and maintain the VRFB system safety, the authors in [142] proposed a model-based-nonlinear optimisation method to manage a variable input power by determining the optimal charge current and flow rate. The goal was to minimise the total energy consumption during the charging process with the SOC, flow rate, input current, and physical constraints. The proposed optimal charging method is solved using the nonlinear optimisation methods (i.e., genetic algorithm and fmincon) in MATLAB/Simulink. Besides the maximum energy harvest, fast charging is another practical issue to satisfy the users' demands. Combining these two objectives, Khaki et al. formulated a multi-objective optimal charging current and flow management for a fast charging and energy-efficient VRFB system in [133]. The charge duration control is expressed as a 2nd-order exponential model in terms of the charging current density and four parameters fitted from the experimental curves. Due to electrolyte flow management and efficiency objectives, the multi-objective optimisation of VRFB is formulated as a comprehensive objective function with three objectives, charging duration control, minimising input energy and minimising pump loss with three corresponding weighting factors.

The model-based nonlinear dynamic optimisation method is efficient in enhancing the system efficiency of a specific VRFB system, both offline and online. However, these methods require an accurate battery model and are not robust against disturbances. Moreover, in MG and more complex power systems, the optimisation of a VRFB system is performed under other higher-level objectives at EMS level, and these model-based methods may not be competitive in these cases for multi-objective optimisation. As for future recommendations, more robust optimisation methods are necessary to handle the aforementioned constraints and handle the uncertainties and observation disturbance during the battery operation.

Conventional controllers. Conventional control algorithms and controller designs have been used to regulate the VRFB's inputs under different conditions. A gain scheduling approach is proposed in [36] to regulate the flow rate considering the OCV changes. In that study, the battery charge/discharge process was modelled by a nonlinear function. Therefore, gain scheduling is implemented with several linear controllers to handle the nonlinearity of the charge-discharge cycle. In [35], the authors proposed an output robust feedback controller to regulate the electrolyte flow rate by determining the optimal reference point for voltage. Bhattacharjee et al. [38] designed a real-time flow rate control integrated with maximum power point tracking (MPPT) controller using common Perturb & Observe (P&O) algorithm. Optimisation of the VRFB system is realised through the proposed integrated MPPT-based CC-CV charging regime with real-time flow rate control to maximise the system efficiency and manipulate the electrolyte temperature variations. These two conventional controllers are simple and effective to manage the flow rate and battery charging process. However, the conventional controllers may have several limitations in handling the optimisation process, which considers the overall power systems with various uncertainties and disturbances. As a result, more advanced real-time controllers must be explored to improve the optimisation performance under more complex power systems while managing the VRFB operation, which explicitly considers the electrolyte flow rate, charging current and thermal dynamics.

4.4. Future direction for VRFB-BMS development

Compared to solid-state batteries such as lithium-ion batteries, advanced methods and algorithms have not yet been explored to improve VRFB's operation. Advanced real-time control techniques are expected to better handle the fluctuations and disturbances in the VRFB system and uncertainties in the battery models. These issues will reduce the accuracy of VRFB models and negatively influence the decision-making process for optimisation. To handle this, fuzzy logic control (FLC) and model predictive control (MPC) are highly applicable for real-time control in a VRFB-BMS. These two advanced real-time control techniques do not require a high-precision battery model and have been proposed and utilised in lead-acid and lithium-ion batteries.

Model predictive control (MPC). MPC is an advanced control algorithm that uses the predictive ability of a system's model to estimate the current state of the system [143]. The objective of the MPC algorithm is to provide an optimal control sequence within a finite time horizon by solving an optimisation problem. Extensive research on single ESS and hybrid power systems shows the applicability of MPC in battery charging optimisation and real-time energy dispatch. In [144], a nonlinear MPC is proposed to minimise charging time for a lithium-ion battery based on a detailed electrochemical battery model. In [145], Xavier and Trimboli introduced a novel application of MPC in a lithium-ion battery to realise cell-level control. The MPC algorithm optimised the battery charging time-based on a 1^{st}-order RC ECM and showed good performance based on a simple ECM. Zou et al. proposed another MPC algorithm for lithium-ion battery optimal charging based on a reduced-order model implemented using partial differential equations [146, 144, 145]. The simulation result show that MPC algorithm can handle the optimal charging problem in a lithium-ion battery with a moderately accurate battery model, which is robust and can be expanded to handle the optimal charging problem in VRFB based on low-precision ECMs.

To study the robust performance of the proposed MPC algorithm for optimal charging problems in single-cell and multi-cell batteries, studies have been carried out in [146, 144, 145]. These studies have shown that an MPC algorithm can solve for optimal charging current under different physical constraints such as temperature, SOC and stack voltage. However, the merits of MPC have not been completely demonstrated in a battery-level system. To further study optimisation using MPC in handling multiple uncertainties and solving inaccurate, nonlinear and comprehensive models, researchers have applied it in hybrid power systems with several components and complex models. In [147], a new adaptive switched MPC strategy is introduced to optimise the operation of power switches in a proposed photovoltaic-diesel battery (PDB) hybrid system [147]. The proposed MPC approach operates differently during charging and discharging, which helps reduce the computational burden using a multi-output and multi-input state-space function for the hybrid power system. Considering the dynamics of a hybrid power system, an adaptive MPC approach is proposed in [148] to handle the uncertainties in the real-time dispatch between the grid and the ESS. The MPC strategies proposed in [147, 148] are expandable to large-scale VRFB-integrated power systems and VRFB-based hybrid storage systems to predict the charging/discharging behaviours of VRFB systems in real-time dispatch. Moreover, these predicted behaviours help the VRFB-BMS in decision-making to find the optimised flow rate and manage the electrolyte temperature, which provides a link between VRFB-BMS and EMS for performance improvement on the battery and power system levels.

Fuzzy logic control (FLC). The FLC is a broadly used method in nonlinear and non-analytical systems. FLC is composed of a knowledge base, and its parameters can be estimated without a precise system model [149]. Many studies explored the application of FLC for lithium-ion BMS to protect the battery from overcharging, over-discharging and realise energy-saving [150, 151, 152]. The benefits of applying the FLC algorithm in lithium-ion batteries are due to the complicated electrochemical characteristics of these batteries, where a general accurate battery model is difficult to formulate [153]. Moreover, human expertise in the battery charging process is hard to be formulated into the usual control rules [153]. Like lithium-ion batteries, the VRFB has complex electrochemical characteristics and thermal dynamics, and conventional ECMs with offline identified parameters are not accurate enough at different flow rates and currents. Besides, the VRFB charging process is influenced by the temperature, flow rate and currents, which increases the complexity of establishing control rules for fast charging and energy-saving. To solve these problems, FLC is applicable in VRFB-BMS for charging optimisation.

In [153], a fuzzy-controlled active state-of-charge controller (FC-ASCC) is designed to optimise the charging process of a lithium-ion battery [153]. Conventional CV methods limit the charging speed using a charging current reduction when the stack voltage reaches a pre-defined limit. The FC-ASCC offers a new adaptive charging strategy with performance improvements compared with conventional CV methods. Another FLC-based charging methodology is introduced in [154] to enhance the fast-charging performance of lithium-ion batteries.

Unlike the FC-ASCC proposed in [153], this charging methodology considered the temperature feedback from a temperature control unit (TCU). The results in this study show a charging time reduction of 9.78% without sacrificing the available capacity and charging efficiency while preventing the battery overheating [154]. These studies provide two valuable examples of achieving battery fast charging with thermal management using FLC, which applies to VRFBs.

5. Energy management system of VRFB-based power systems

5.1. Overview

As outlined in the previous sections, VRFB seems to be a great large-scale ESS. The main application of VRFB could be in MG with different RES. However, due to the high cost of components (particularly the ESSs) and the complexity of MG operation under various sources of uncertainties, a higher level EMS is needed to coordinate components operation at local levels [42]. This need intensifies in islanded microgrids (IMG), where careful frequency and voltage regulation and stability are highly anticipated due to intermittent RES generation and low system inertia [44]. As explained in Section 4, a BMS is a local monitoring and control unit, while an EMS operates the energy system as a whole to minimise the MG overall operational cost and maintain the dynamic and steady-state frequency and voltage stability [42]. As a result, an EMS should be capable of generation and storage scheduling based on economic, reliability and resiliency constraints, load management and online monitoring.

In the following subsections, we review state-of-the-art EMS for VRFBs and recommend future development for EMS in VRFB systems.

5.2. State-of-the-art VRFB-based EMS

In [44], a novel IMG-EMS was proposed to optimise the energy and reserve scheduling of a VRFB with controlled distributed generators. The main objective of the IMG-EMS was to minimise the operational cost of the IMG while preserving the frequency stability and ensuring efficiency [44]. Moreover, a linear VRFB model was used in the EMS to approximate the non-linear characteristics of the VRFB system. The MG optimisation problem was formulated as a two-stage stochastic mixed-integer linear programming (MILP) problem to obtain the global optimal solutions [44]. Foles et al. addressed the integration of PV-VRFB, and the development of an effective EMS for the hybrid MG in UÉvora [47]. The significance of this work is that they used the VRFB to smooth the output of PVs and maintain the ramp rate within a pre-defined range [47]. Lee et al. discussed a real MG located in Daejeon, South Korea, and developed an EMS to optimise the VRFB-ESS operation. This research focused more on studying the economic feasibility of an office building as a MG. They showed that their EMS could achieve low operation cost and optimal energy management to overcome the low-efficiency problem of VRFBs [11]. Another EMS is introduced in [48] to realise optimal power dispatch of the VRFB-ESS, PVs and distributed generation (DG) units in an IMG. The energy management problem was formulated as an optimisation problem to minimise the total operational cost by frequency regulation and peak shaving and solved by particle swarm optimisation (PSO) [48]. In [49], an application of VRFB is explored for an EV charging station that is powered by a PV system. The developed EMS used VRFB to improve the overall system's efficiency and reduce strain on the MG by using a hybrid EKF (HEKF) algorithm [49]. The results showed that the HEKF-based EMS could optimise the charging process considering other parameters, such as PV power estimation, EV user's demand, and EV configuration from a database [49].

The VRFB-based EMSs in the literature have one thing in common: one type of renewable energy supply and the VRFB as the sole type of ESS considered in the MG. However, it is known that a mix of RESs could significantly enhance the utili-

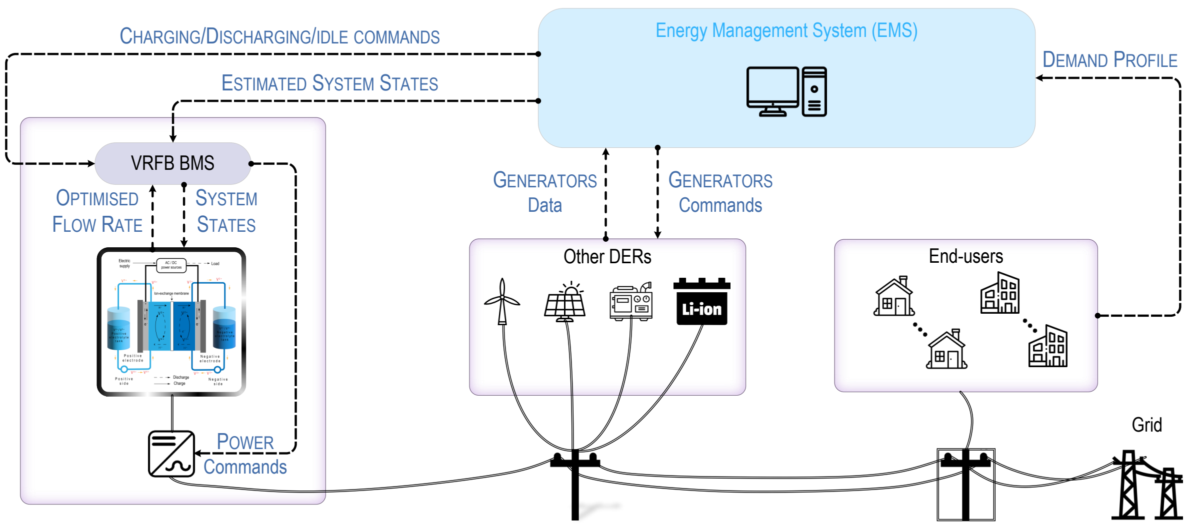


Figure 8: A hypothetical collaborative BMS-EMS scheme for a generic MG

sation of renewable energy in a more cost-effective way, particularly in rural and remote areas. In [45], a novel EMS for hybrid RES-MG and VRFB-ESS was developed to effectively manage the cost of demand, shave the peaks and optimally schedule the components within the MG comprising a 10 kWp solar PV system, 1 kW wind turbine, and 15 kVA biogas engine generator. This study demonstrated a scalable and generalised commercial EMS, which is claimed to be applicable for other large-scale hybrid RES-MGs [45]. Another hybrid RES-MG case study with solar PV, wind turbines and a biogas engine generator was studied in [75] investigating the application of an EMS to achieve zero loss of power supply probability. The proposed EMS considered the intermittency of the renewable sources, operation and maintenance costs and revenue generation to form an intelligent scheduling system and real-time controller for loss reduction [75]. With the development of the internet of things (IoT) technology, Samanta et al. in [12] proposed an optimised energy management scheme for an integrated hybrid MG using a low-cost IoT-based smart communication platform. The study used previously studied hybrid RES-MG, and the IoT-based EMS showed flexibility in smart scheduling and optimisation. A hybrid random forest (RF) and coral reefs optimisation (RFCRO) algorithm is proposed in [46] to manage the power flow between a wind turbine, PV array, VRFB and fuel cell by establishing an overall cost function. In this study, the RF aims to predict the load demand, and CRO optimises the MG configuration from the predicted load demand [46]. Simulation results showed the proposed hybrid RFCRO EMS improved the MG's productivity, efficiency and power quality. Also, the proposed method outperformed other approaches, namely bacterial foraging optimisation - artificial neural network (BFOANN), Ant lion optimisation (ALO), grasshopper optimisation algorithm Pi sigma neural network (GOAPSNN) and radial basis function neural network- slap swarm algorithm (RBFNN-SSA), with faster convergence and higher accuracy [46].

5.3. Recommendations for future development of EMS

In [44, 47, 11, 48, 49, 45, 75, 12, 46], various EMSs are developed for different power systems that integrate with VRFB. These studies demonstrate the importance of the EMS to manage the energy system operation for profit maximisation, smoothing the PV power, overcoming the low-efficiency problem of the VRFB system, optimising the charging process of VRFB and so on. However, only a few papers considered the link between EMS and BMS; hence, resulting in suboptimal outcomes. For instance, in [44], the maximum power of a VRFB and a range of SOC are considered in a simplified non-linear model as the physical constraints of the VRFB system in the EMS, and the electrolyte temperature and flow rate are neglected in operation. Therefore, the efficiency of the VRFB system may decrease and even cause an emergency shutdown. A similar situation can arise when the EMS only considers the objectives of the whole power system without taking into account VRFB's specific requirements and constraints. Moreover, in [126], Trovo et al. identified the thermal precipitation and energy losses issue caused by standby conditions during the long-term operation of VRFB systems. The design of two standby modes in the VRFB-BMS is important to provide fast power service for the end-users [126]. A standby period can be predicted by the EMS using historical data, which assists the BMS in determining the timing of different modes. Integrating the EMS and BMS is an efficient solution to overcoming these issues. With advanced state estimation and optimisation techniques, the BMS can provide accurate state estimation feedback to the EMS, which maximises the system efficiency and maintains the electrolyte temperature within a safe limit.

In Fig. 8, a collaborative BMS-EMS scheme is proposed to enhance the performance of both the power and VRFB systems. This approach utilised the overall data monitoring/analysis, forecasting, and optimised control features of the EMS in the power system, together with the real-time advanced state estimation, optimisation and thermal management of the BMS in the VRFB system. The EMS receives the predefined objectives from manual instructions and data analysis from distributed energy resources (DERs)/end-users to forecast the demand/supply. The predicted values are used by different decision-making algorithms to optimise the operation. Besides, the forecast values can be utilised by the VRFB-BMS to estimate the optimal flow rate in future intervals and predict the thermal dynamics. In other words, sharing the forecast results with the BMS allows it to realise predictive control, make optimal decisions, and protect the battery over a broader time horizon. Another benefit of linking BMS and EMS is that the advanced system state estimation technique built in the VRFB-BMS provides the EMS with more accurate SOC and capacity estimation as physical constraints for decision-making. Suppose the VRFB system reaches a high/low SOC level. In that case, the EMS can recognise this issue and prepare to command another battery for energy storage/distribution. This prevents overcharging/discharging issues in the VRFBs and maintains the sustainability of the energy supply chain.

6. Conclusion

In this review article, VRFB's working principle, current commercial products, features and applications in power systems are presented at the beginning for a general overview of VRFB technologies. The applications of the VRFB in MG, residential and community storage and renewable power plants illustrate the potential of the VRFB system in power smoothing, energy storage, peak shaving and other applications. Contemporary challenges are identified and analysed to highlight the importance of a well-developed battery model for accurate state estimation and application in advanced optimisation/control algorithms. Four types of VRFB models are reviewed and evaluated to show their merits and constraints. An additional review is conducted to outline seven critical functionalities for a well-design VRFB-BMS. Then, state-of-the-art techniques for state estimation and advanced control techniques are reviewed from VRFB-related literature to demonstrate their potential. Besides, two advanced real-time control methods are introduced to recommend a future development roadmap for VRFB-BMS. Finally, several VRFB-based EMS are reviewed, and the importance of a link between BMS and EMS has been identified to achieve a more solid performance within the VRFB and hybrid energy system. Here is a summary of the significance of this review paper:

- Eight types of VRFB losses are summarised to give readers an overall understanding of which factors in battery design and operation may significantly impact the battery efficiency performance.
- Current applications of VRFB are reviewed and categorised into three aspects, and their functions are introduced.
- Contemporary challenges in the development of VRFB are identified and analysed based on previous literature and our studies.
- Mainstream VRFB models are studied, analysed and summarised to show their strengths and weaknesses in different applications.
- Based on the study of other solid-state batteries, a hypothetical BMS approach is proposed that takes into account the unique attributes of VRFB batteries.
- Advanced optimisation and system state estimation techniques are reviewed. Future development recommendations for real-time control are presented to show the path to improving the current VRFB-BMS design.
- Several VRFB-based EMS are reviewed, and a new collaborative BMS-EMS scheme for VRFB-based power systems is proposed to enhance the performance of both the power systems and VRFB itself.

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