Consensus Algorithms and Deep Reinforcement Learning in Energy Market: A Review

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***Abstract*—Blockchain (BC) and artificial intelligence (AI) are often utilised separately in energy trading systems (ETS). However, these technologies can complement each other and reinforce their capabilities when integrated. This paper provides a comprehensive review of consensus algorithms (CA) of BC and deep reinforcement learning (DRL) in ETS. While the distributed consensus underpins the immutability of transaction records of prosumers, the deluge of data generated paves the way to use AI algorithms for forecasting and address other data analytic related issues. Hence, the motivation to combine BC with AI to realise secure and intelligent ETS. This study explores the principles, potentials, models, active research efforts and unresolved challenges in the CA and DRL. The review shows that despite the current interest in each of these technologies, little effort has been made at jointly exploiting them in ETS due to some open issues. Therefore, new insights are actively required to harness the full potentials of CA and DRL in ETS. We propose a framework and offer some perspectives on effective BC-AI integration in ETS.**

***Index Terms*—Deep reinforcement learning, blockchain, energy market, markov decision process, consensus algorithm, distributed ledger technology, artificial intelligence**

NOMENCLATURE

A2C	Advantage Actor Critic
A3C	Asynchronous Advantage Actor Critic
AI	Artificial Intelligence
BC	Blockchain
BFT	Byzantine Fault Tolerance
CA	Consensus Algorithm
CNN	Convolutional Neural Network
DAG	Directed Acyclic Graph
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resources
DL	Deep Learning
DLT	Distributed Ledger Technology
DNN	Deep Neural Network
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
DSR	Demand Side Response
ETS	Energy Trading System
FPP	Federated Power Plant
LSTM	Long Short-Term Memory
MDP	Markov Decision Process
ML	Machine Learning
P2P	Peer-to-peer
PoA	Proof of Authority
PoAc	Proof of Activity
PoB	Proof of Burn
PoC	Proof of Capacity
PoET	Proof of Elapsed Time
PoI	Proof of Importance
PoS	Proof of Stake
PoW	Proof of Work
RDPG	Recurrent Deterministic Policy Gradient
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SL	Supervised Learning
SVM	Support Vector Machines
USL	Unsupervised Learning

I. INTRODUCTION

Recent market research by PwC predicts that AI will add up to 15.7 trillion to the world economy by 2030 [1] while Gartner forecasts BC value addition to increase by 3.1 trillion by same year [2]. Accordingly, the last few years have witnessed rapid advancements in many enabling technologies including communication systems, battery systems, cloud computing, IoT, big data analytics and many more. These developments have not only laid the foundation for the transformative technologies seen in the energy sector today but also accelerated the transition of energy consumers to prosumers. Thus, energy prosumers now have abilities to produce, consume, store and trade energy [3]–[6]. This is the underpinning of energy trading in smart grid.

While transactions in energy trading systems (ETS) are digitally enabled, they also create an unprecedented amount of data for which traditional processing techniques are unsuitable. For instance, the 27 million domestic electricity consumers in the UK would require to process 50 terabytes of data or 500 billion data-points annually when the smart meters are fully deployed [7]. Moreover, variability of prosumer's demands, flexibility of consumption, and generation uncer-

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tainty are additional challenges that create bottlenecks when solving decision, control, security and privacy problems. The application of artificial intelligence (AI) and BC, either in isolation, or jointly has been relatively efficient in solving data modelling and security challenges in vertical applications [8]. Hence, their adoption is increasing in energy networks; ranging from energy management [9], [10], demand response [11], [12], operational control [13], [14], energy trading [15]–[17], security and transaction management [18], etc.

AI has transformed many industries, improving predictive accuracy by learning from the available historical data. Machine learning (ML) algorithms have helped industries to predict user activities, understand consumption and purchasing patterns as well as provide recommendations and contents according to individual users' preferences. AI systems are powered by ML algorithms using supervised, unsupervised, and Reinforcement Learning (RL) approaches [19]. Deep Learning (DL) is an advanced ML method that employs multiple processing layers to learn hierarchical representations of data with different levels of abstractions [20]. Supervised Learning (SL) requires input data and corresponding labels. Supervised ML algorithms include Decision Trees (DT), Support Vector Machines (SVM), Naive Bayes (NB), K-Nearest Neighbour (KNN), Random Forest (RF), Association Rule (AR) and Ensemble Learning (EL); and Deep Neural Network (DNN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) are supervised DL algorithms. Unsupervised Learning (USL) processes input data without labelled responses. Principal Component Analysis (PCA) and k-means clustering are unsupervised ML algorithms while Deep Autoencoder (DAE), Restricted Boltzmann Machines (RBM), and Deep Belief Network (DBN) are examples of unsupervised DL algorithms. RL trains an agent to take actions in a given environment to maximise pre-defined reward. Deep Reinforcement Learning (DRL) is a combination of both DL and RL and has been shown to outperform other classical ML prediction methods in terms of accuracy, high computational power, convergence speed, and long-term forecasting [21]–[23].

DRL is a powerful, yet simple algorithm that helps an agent to optimise its action for maximum reward by exploring or transitioning between states and actions [24]. However, in a practical energy market that consists of multiple actors (prosumers, producers, consumers, traders, distribution system operators, etc.) with different states and actions, both the memory and time required for state transitions would increase with number of roles and states. Although AI provides planning, learning, reasoning, and problem-solving properties, trust, explainability, and privacy of the historical data for learning and prediction are ongoing debates [25]. Besides, transaction management among the different entities in the energy market is still an open issue that needs addressing. For example, information about prosumers generated during energy trading contain sensitive information. Thus, uncontrolled disclosure or access can lead to violation of privacy and trust or even attack.

These challenges motivated the consideration of other disruptive technologies like BC for energy trading applications. BC is a trustful framework to support real-time security and transaction management in a distributed network. BC is a distributed ledger technology (DLT), maintained by the network participants in a virtual peer-to-peer (P2P) network. Sometimes, the structures of DLT are not always a block of chains but can exist as a distributed acyclic graph (DAG) [8], [26] as seen in IOTA. BC adopts a variety of mechanisms to manage and share transactions across the distributed authorised nodes. These mechanisms are essentially the distributed consensus algorithms that determine the scalability, transaction time, and efficiency of the BC solution [18]. In general, BC manages transactions, authenticates trades as well as ensures privacy and security of participants' data to reduce transaction cost and improve efficiency. Thus, integrating BC with AI ensures privacy, trust and security of prosumers' information are preserved in ETS. However, BC faces some challenges including scalability and efficiency in terms of transaction speed and consensus delay [25]. These challenges can be addressed by integrating AI to build a ML system on BC for improved security, scalability and more effective personalisation and governance [25] as well as faster consensus.

Combined AI-BC solutions have been demonstrated in many sectors [25], [27], [28]. Although significant research effort are made at adopting AI [22], [24] or BC [18] separately, combined AI-BC technologies are still limited in energy networks, aside the few cases reported in [29]–[31]. This work focuses on the application of combined AI-BC algorithms in ETS - a contrast to previous works which reported AI-BC solutions in other vertical applications and industries [8], [25], [32], [33]. Specifically, the energy trading requires analysis of large volumes of diverse data for real-time or near real-time response to market changes. Thus, sophisticated AI algorithms and other emerging technologies are required. In this regard, consensus algorithms (CA) of BC and the learning algorithms of AI are the core components of their respective technologies and are discussed extensively in this paper. The contributions of this work are summarised as follows:

- a comprehensive review of the recently proposed BC and AI-based solutions in transactive networks after which we establish the benefits of AI-BC enabled trading in energy market;
- we present our views and inferences from previous review works, following the discussion of the working principle of DRL and comparative analysis of existing algorithms;
- characterisation and working review of CA algorithms, their operations and suitability for co-implementation with AI;
- proposal of new AI-BC framework to reinforce security and intelligent capabilities of ETS by further exploiting the potentials inherent in both technologies;
- summary of open research challenges and future research direction.

The outline of the review is shown in Fig. 1, while a comparative analysis to existing surveys and applications of AI and

BC is summarised in Table I.

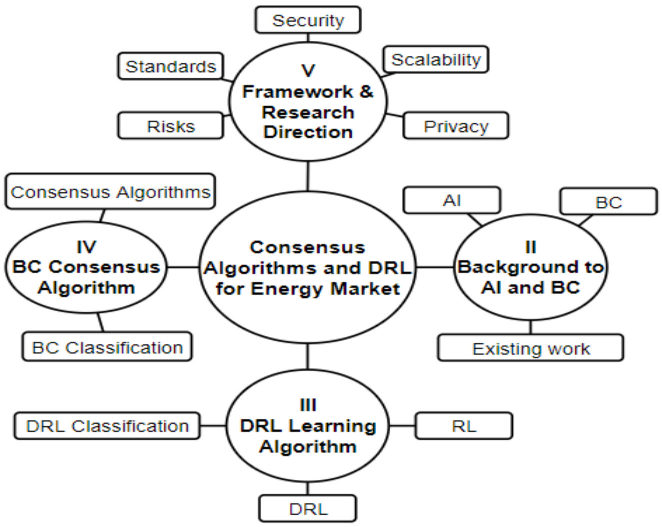

Fig. 1. Overview of the Review

A brief background to AI and BC is provided in Section II with a focus on the learning algorithms and consensus algorithms, as well as a review of other schemes and existing research on their integration. A detailed concept of DRL with its mathematical modelling and related research are presented in Section III, followed by the working principles of BC CA and related research in Section IV. Framework and open research challenges of both technologies in the energy market are discussed in Section V, while Section VI concludes the paper.

II. Background

This section presents overviews of the DRL algorithm, BC CAs, a review of other schemes and the existing research work on AI and BC technologies.

A. Artificial Intelligence: Deep Reinforcement Learning

AI in general embodies the study of intelligent machines perceived to perform tasks akin to human intelligence. These tasks may be reward-based, where a particular action in an environment maximises the chances of success [24]. AI systems are powered by ML which includes, SL, USL, DL, and RL [19]. ML involves structural data analysis comprising both linear and nonlinear variables, mostly formulated for classification (SL) and clustering (USL) problems using algorithms such as SVM. DL, on the other hand, involves multi-variate data analysis and learning based on artificial neural networks (ANN) [37], such as, CNN and long short-term memory (LSTM). RL dynamically learns from the environment by adjusting actions based on feedback to maximise reward. Most AI-based applications focus on the use of data to make intelligent decisions by utilising ML, reasoning, natural language processing, and planning [19] (depicted in Fig. 2), with active research effort into applying the intelligence to solve real-life problems. For instance, key enablers of the electricity

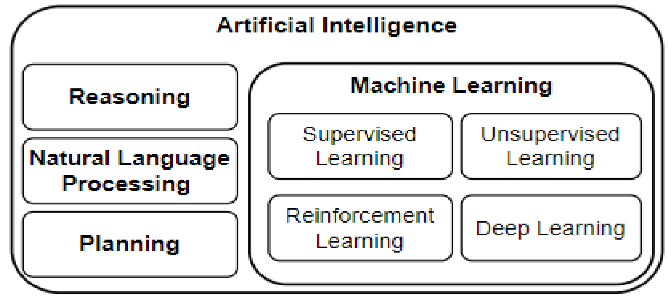

Fig. 2. Overview of AI and ML relations, adapted from [19]

market is energy storage system (ESS) as it provides means of flexibility. Applying AI in storage system improves decisions to store excess energy surplus production and discharge it to meet demand at a later time while considering different constraints including load forecast, generation capacity, prices, etc. These decisions would provide more efficient ways of maximising DER integration, minimising electricity prices, and maximising returns to the storage owners.

RL and DRL have found applications in the energy market, ESS, and generation optimisation, with intelligent decisions mostly formulated as a Markov decision process (MDP) [9], [15], [38]–[41]. With MDP, a microgrid makes decisions using the current state - comprising of the current/predicted battery level, generation capacity, demand flexibility, and the Q-function for each state-strategy pair. For instance, in the energy market, a large amount of uncertainty can be learned by RL for real-time decision making on the optimal price to bid/offer a kWh of energy or the appropriate time to sell/buy energy. In RL, prosumers can participate in trading actions without extensive analytical calculations and wide knowledge of the market model [42].

B. Distributed Ledger Technologies: Consensus Algorithms

Like the traditional database system, DLT is distributed database that stores ledgers and transactions. DLT however adopts several mechanisms in its data storage and sharing by distributing the records over multiple connected nodes to overcome the single point of failure of the traditional database system. DLT structures could be in the form of a block of chains refer to as BC or a DAG found in IOTA. For consistency throughout the paper, BC is used to indicate the different classes of DLT based on community consensus.

BC are immutable ledgers, where newly created blocks, verified by its members using consensus algorithms are cryptographically linked to the previous block in the chain. The main features of BC include decentralisation, immutability, auditability, transparency, anonymity, and security. A systematic review of BC technology to the smart grid is provided in [18], [43], while a working overview of the process of creating a block and attaching it to the chain is shown in Fig. 3. Fig. 3a illustrates the BC DLT while Fig. 3b illustrates the DAG DLT.

Irrespective of the structure of the DLT, the CA used in creating the new blocks determines the efficiency, robustness,

TABLE I
COMPARATIVE STUDY OF EXISTING SURVEYS ON BLOCKCHAIN AND AI WITH THIS STUDY

Technology	Ref	Year	Objective	Use-case
BC	[18]	2018	Systematic review of challenges and opportunities of BC technology in the energy sector	Energy Sector
BC	[34]	2020	Overviews and highlights the benefits of BC and smart contracts in the energy sector	Energy transaction
BC	[35]	2020	Discuss the potential and applications of BC in the internet of energy management	Energy management
BC	[36]	2019	Review the deployment of decentralised transactive energy systems to propose a DLT based management infrastructure	Energy Transaction
AI	[24]	2019	Reviews models, algorithms and techniques of DRL for Power system	Power system
BC and AI	[25]	2018	Summarised the existing efforts with discussion on the promising future of integrating both technologies	N/A
BC and AI	[27]	2019	Proposed a BC-based distributed software-defined vehicular ad hoc networks (VANET) framework using dueling deep Q learning approach to establish a secure architecture for VANET coordination	Vehicular networks
BC and AI	[28]	2019	Proposed DRL-based performance optimisation framework for blockchain-enabled industrial IoT systems	Industrial IoT
BC and AI	[8]	2020	Surveys existing works for BC and ML technologies for communications and networking systems	Communications and networking systems
BC and AI	[32]	2019	Surveys BC applications for AI in cyber-physical systems	Cyber-physical systems
BC and AI	[33]	2019	Surveys ML adoption for making BT-based smart applications resilient against attacks	Smart applications
BC and AI	This study		Surveys the consensus algorithms of BC and the learning algorithms of AI to ease implementation for use in energy market	Energy transaction

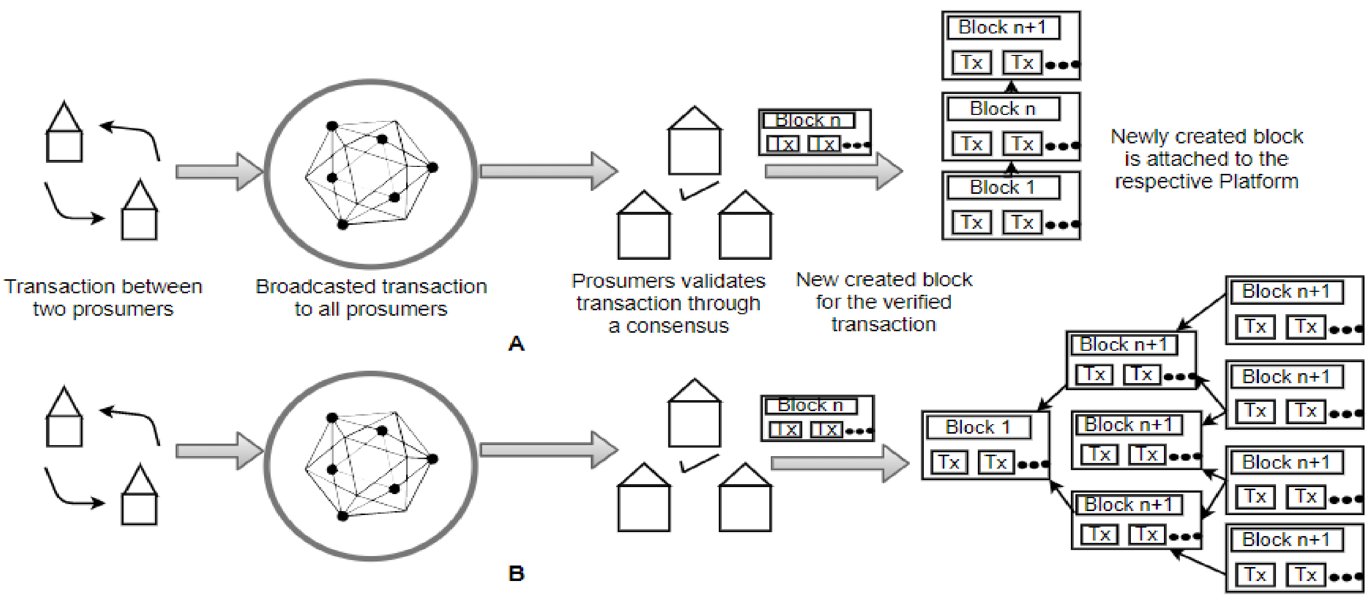

Fig. 3. The process of creating a block and attaching to the respective platform: A for blockchain; B for directed acrylic graph.

and security of the BC technology [44]. The CA is perhaps the most crucial aspect of the whole BC system as poor choice or modelling can result in the BC failure. Achieving consensus particularly in a diverse distributed system is challenging. Thus a CA should be resilient to nodes failure, message delays, corrupted messages, and malicious nodes. Consensus models are continuously been developed to ensure a more secure and robust BC system. A classification of the consensus algorithms including their pros and cons and usage in the energy network are further discussed in Section IV.

1) Smart Contracts: For transactions among different entities to be valid, there exist trading contracts that set out the rules of trade. In BC technology, the set of rules that govern a transaction is termed a smart contract, which is a digital agreement among the parties involved [45]. It involves the set of rules governing their interactions relating to how and when to trade, who should be involved, and how payment should be processed. It is usually executed as a program to control and enforce the transfer of digital currencies in exchange for assets between involved parties in the BC network [46].

Smart contract codes are executed by the BC mining nodes to determine the legitimacy of a transaction. BC platform like Ethereum, Hyperledger Fabric, etc. are platforms that enable the programming of the smart contract.

As BC offers the advantage of decentralisation and secured data transmission, it mainly acts as an accounting tool and does not incentivise real-time behavioural changes like demand response and load shifting which are crucial to grid balancing. Thus, AI can be useful in that aspect. The benefits of integrating both technologies and the advantages over other technical schemes for energy market are further discussed in the next section.

C. *Technical Schemes Versus AI-BC Enabled Energy Market*

The potential mass deployment of DER increases power sector complexity and the need for flexibility, thereby creating an opportunity for integrating new tools for system optimisation and energy trading. Energy system optimisation including trading is an on-going challenge fuelled by the increasing connection of DERs to the grid, where different solutions and models are regularly being proposed in the literature. These solutions can be categorised into four technical approaches. These are 1) game theory, 2) constrained optimisation, 3) auction theory, and 4) BC [47]. In game theory, a mathematical tool is developed to analyse the strategic decision making of players/prosumers in a competitive environment, where the decisions made directly affect the actions of other players. Notably, this game theory involving cooperative and non-cooperative games has been used to reduce the cost of energy [48]–[51], energy balancing [52], [53], and incentivising energy trading participation [54]. Most solution models under the constrained optimisation approach involve mathematical programming including linear or nonlinear programming, mixed integer programming, dynamic programming, or alternating direction method of multipliers with set objectives to minimise cost [55], improve efficiency [56], or for optimal energy schedule [57]. In auction theory, prosumers who wish to buy and sell energy interact to trade, where sellers and buyers submit their asks and bids prices respectively. Similarly, auction theory has achieved the objective of local energy balancing [58]–[60]. As security is not designed by default during energy trading, a way to incentivise more participation and to secure energy trading transactions is to create a secured trading platform for participants [61]. To this, BC models including Hyperledger [62], Elecbay [63], smart contracts [52], [64], and Ethereum [65] are proposed for secured energy trading.

Although energy trading is achieved with these four technical approaches, each on its own is not sufficient to create an energy market involving a multitude of prosumers. Besides, the game theory and constrained optimisation models relatively requires a high level of mathematical knowledge and are not secured by design. In addition, the dynamics of energy market involving forecasting demands, predictions, and flexibility provisions can only be achieved by the combination of several traditional methods, which makes individual method limited in its deployment. Thus, a joint integration of BC and AI as proposed in this study would create a secured, and reliable energy market system [66]. Table II summarised the comparative analysis of the previous energy trading schemes and the proposed AI-BC energy market.

TABLE II
COMPARATIVE STUDY OF EXISTING SCHEMES ON ENERGY TRADING WITH THIS STUDY

Technical Approach	**Ref**	**Year**	**Prediction & forecast**	**System Optim.: Energy Market**	**Security & Privacy**
Game Theory	[48]–[54]	2019	No	Yes	No
Constrained Optimisation	[55]–[57]	2018/ 2019	No	Yes	No
Auction Theory	[58], [60]	2020	No	Yes	No
Auction Theory	[59]	2019	Yes	Yes	No
Blockchain	[35]	2020	No	Yes	Yes
AI-BC Energy Market		2020	Yes	Yes	Yes

D. *Existing Research on AI-BC Integration*

Combined AI-BC technologies in vertical applications and energy network are gaining traction. A DRL method is proposed in [67] for payment-privacy protection level game in crowdsensing. Study [68] summarised the existing efforts on BC and AI integration with a discussion on the promising future of both technologies. The authors in [8] surveyed existing works for BC and ML technologies for communication and networking systems, discussing the benefits, applications, open issues, challenges, and broader perspectives for integrating both technologies. Similarly, [32] surveyed BC applications for AI in various cyber-physical systems including energy network. They also identified open research challenges of utilising BC for AI and discussed platform protocols targeting AI. ML adoption in BC-based smart applications resilient against attacks is further investigated in [33] while demonstrating a case study of an energy trading system implementing both AI and BC.

Beyond surveys, some notable works on integrating both technologies are found in [27], [28], [31], [69], [70]. Specifically, [28] proposed a DRL-based performance optimisation framework for BC-enabled industrial IoT system. Study [27] integrated both AI and BC technologies in VANET by proposing a BC-based distributed software-defined framework using a duelling deep Q learning to establish secure VANET coordination. The authors in [69] designed and developed an IoT architecture with both BC and AI to support an effective big data analysis. Finally, in energy network, study [70] presented a decentralised AI-BC based energy cloud management architecture, while [31] proposed a deep learning and BC-based energy framework. In the proposed scheme, the deep learning serves as an intrusion detection system for detecting network attacks whilst utilising the generation of blocks using short signatures and hash functions to stop cyber attacks on SGs. Table I summarised the comparative analysis of existing surveys to this study.

The transparency and auditability features of BC ensures reliability while immutability and consensus reinforce the trust in the AI decision-making process [8]. Moreover, in terms of the energy network, AI can enable fast and intelligent decision making, for increased grid flexibility and renewable integration. Areas of application of both technologies in energy network include wind and solar generation forecast, grid stability and reliability, demand forecast, demand side management, optimised energy storage, and market design and operations [71]. Other potential benefits of leveraging BC for AI-based energy market including improved trust in AI-based decision, decentralised intelligence and high efficiency, are presented in Table III. A framework of harnessing the potential of both technologies is proposed and discussed in Section V.

TABLE III
BENEFITS OF BLOCKCHAIN AND AI FOR ENERGY MARKET [8], [32]

Properties of Blockchain	**Properties of Artificial Intelligence**	**Integration Benefits**
Distributed ledger technology	Data and model sharing	Increased data control and training
Data immutability	Depend on reliable data	Increase trust in data modelling
Decentralised communication	Decentralised intelligence	Secured data communication and sharing
Consensus agreement	Trust for decision making	Collective decision making
Timestamped property	Auditability	Auditable data providing more trust on AI application

III. Deep Reinforcement Learning: Overview

Following the overview of both technologies in the previous section, this section discusses in detail the transitioning of RL to DRL, it's mathematical modelling, algorithms, and works reported in the literature on RL/DRL, with focus on flexibility in the energy market.

A. Mathematical Modelling of Reinforcement Learning

In its basic form, a RL algorithm trains an agent interacting in its environment, transitioning through different states utilising different actions. The main aim of the agent is to maximise its total reward by using different strategies or policies. DL is a classical ML algorithm that utilises multiple layers to extract information from the data input. Thus DRL illustrated in Fig. 4. combines the perception function of DL with the decision making ability of RL [24].

RL modelling usually follows a MDP, satisfying Markov's property which highlights that the current state within an environment only depends on the previous state. In turn, the future state is a consequence of its current state. The MDP defines the environment in which the agent interacts, and it is defined as a tuple of (S, A, P, R, γ) where S is the state, A is the agent, P is the probability matrix, R is the reward function and γ is the discount factor. The definitions of all mathematical variables are presented in Table IV.

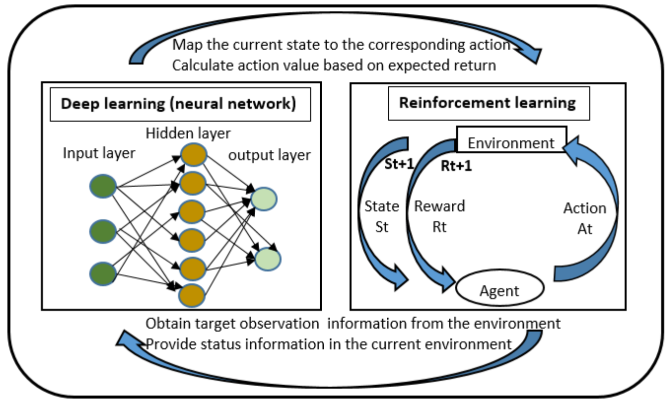

Fig. 4. Deep Reinforcement Learning (adapted from [24])

TABLE IV
LIST OF MATHEMATICAL VARIABLES AND THEIR DEFINITIONS

Variable	**Definition**	**Variable**	**Definition**
S	state	γ	discount factor
A	action	α	learning rate
P	probability matrix	θ	target network
E	environment matrix	ϕ	data-batch samples
R	reward function	ω	weight
G	return function	V	value function
D	trading replay memory	π	policy
N	capacity	Q	action-value function
L	loss function	SoC	state of charge
t	time		

Formulating energy network as an MDP, the state S consists of a time component, load component, generation component, state of charge (SoC) of battery, and the energy price [9]. The time component refers to the hourly, half-hourly, daily, or yearly information, which depends on the problem model. For instance, the time component provides information to learn about energy production or consumption pattern. The load refers to any load component in the model, such as electrical load to thermal load, etc. SoC is a controllable component that provides flexibility which is constraint by (1). i.e. maximum, and minimum charging limit of the storage capacity.

$$SoC_{min} \leq SoC \leq SoC_{max} \tag{1}$$

The price component determines the cost of electricity (buy/sell). The price component could provide some cost savings if the model considers the time of use pricing (peak and off-peak).

The agent A in the MDP tuple represents the actors participating in the energy market. The reward function R is the incentive provided when some actions are performed. For instance, reduction in cost by shifting energy consumption to the off-peak period or cost saved when using a battery storage device rather than grid consumption.

The state transition probability from initial state S to next state S' with action a at time t is described as:

$$P^a_{ss'} = P[S_{t+1} = S' \; S_t = s, A_t = a] \tag{2}$$

where action a in an energy network could include charging or discharging a battery, load shifting, decision to trade energy, etc.

B. Value-Reward Function and Policy

The agent in the environment uses the reward function to learn how to interact in the environment. The reward function maps state and action to their rewards, and it is expressed as

$$R^a_{ss'} = E[R_{t+1} \; S_t = s, A_t = a] \tag{3}$$

A return function G_t exists that maps state to reward, define as the discounted sum of rewards from each time step t. It is expressed as

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \tag{4}$$

where, the discounted factor, γ is expressed as

$$\gamma \in [0, 1] \tag{5}$$

Further, the value function V_π is the expected return from the states. This describes the benefits of being in a state, under a policy π and it is described as

$$V_\pi(s) = E_\pi[G_t \; S_t = s] \tag{6}$$

Similarly, an action-value function Q_π exists that expresses the return for taking action a in state S using policy π described as

$$Q_\pi(s, a) = E_\pi[G_t \; S_t = s, A_t = a] \tag{7}$$

where policy π defines the behaviour of the agent in the MDP, which maps state s to the probability of taking action a, formally expressed as

$$\pi(a|s) = P[A_t = a|S_t = s] \tag{8}$$

C. Reinforcement Learning: Q-Learning

In Q-learning, the agent performs the actions that will generate the maximum reward. The total reward is called the Q-value, expressed as the Bellman equation as

$$Q(s, a) = R(s, a) + \gamma \max_a Q(s', a) \tag{9}$$

Equation (9) presents the Q-value of state s and action a as the immediate reward $R(s, a)$ plus the maximum Q-value from the next state s'. The Q-value function provides the expected discounted long-term reward of a MG from an energy trading decision in a time-slot. Equation (9) can be further expressed as the Bellman iterative equation as

$$Q(s, a) = Q(s, a) + \alpha[R(s, a) + \gamma \max_a Q(s', a') - Q(s, a)] \tag{10}$$

where α is the learning rate or step size. The Q-learning algorithm is illustrated in Algorithm 1.

Algorithm 1: The Q-Learning Algorithm.

Initialise Q-values $Q(s, a)$ arbitrarily for all state-action pairs
for *each step until learning stopped* **do**
  Choose an action a in the current state s based on Q-value estimate $Q(s, .)$
  Take the chosen action a and observe the outcome state s' and reward r
  if s' *is terminal* **then**
    target = $R(s, a, s')$
    sample new initial state s'
  else
    target = $R(s, a, s') + \gamma \max_{a'} Q_t(s', a')$
  end
  Update $Q_{t+1}(s, a) = (1-\alpha)Q_t(s, a) + \alpha[R(s, a, s') + \gamma \max_{a'} Q_t(s', a')]$
  Go to next state
end

Algorithm 2: The Deep Q-Learning Algorithm with Experience Replay [42], [72].

Initialise trading replay memory D to capacity N
Initialise Q with random weights ω
for *each episode until learning stopped* **do**
  Collect the current market, ESS and demand conditions
  Forecast the renewable generation output
  Initialise sequence $s_1 = x_1$ and preprocessed sequence $\phi_1 = \phi(s_1)$
  for *each time step of the episode* **do**
    Select a random action a_t with probability ϵ
    otherwise select a_t = $arg \max_a Q(\phi(s_t), a; \omega$
    Execute a_t and observe reward r_t
    Set $s_{t+1} = s_t, a_t, x_{t_1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Sample random minibatch of transition from D
    Set $y_j = \begin{cases} r_j, & \text{for terminal} \phi_{j+1} \\ r_j + \gamma max'_a Q(\phi_{j+1}, a'; \omega), & \text{otherwise} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_{j+1}, a'; \omega))^2$ for the network parameters ω
    Reset Q
  end
end

D. Transitioning from RL to DRL

To deal with the high dimensionality of state-action transitions of multiple prosumers typical in the energy network, a neural network is used to approximate the Q-value function. DRL extends RL by using deep neural networks (DNN) without explicitly designing the state space. The objective of the neural network is to reduce the error in the weights ω. Here, we train the Q-network by minimising a sequence of loss functions $L_t \omega_t$ over the iteration t. Using (10), the error function is calculated as the difference between the maximum possible value from the next state (Q_target) and the Q_value (current prediction) expressed in (11)

$$L_t(\omega_t) = E_{s,a,s',r\sim D}\left[\theta_t - Q(s,a;\omega_t)\right]^2 \tag{11}$$

where $\theta_t = r + \gamma \max_a Q(s', a; \omega_{t-1})$ is the target for iteration t. Equation (11) samples the environment and stores the observed experiences in a replay memory, then a small batch is selected for learning using a gradient descent update step. The full deep Q-learning pseudocode with experience reply is illustrated in Algorithm 2, which is usually used to accelerate the Q-learning process especially for a large number of MGs by extracting features from the high-dimension state-action space in smart grid (SG) [9]. Table V presents a summary of the differences between RL and DRL.

TABLE V
COMPARING RL TO DRL [42]

Properties	Reinforcement learning	Deep reinforcement Learning
Learning algorithm	Q-learning	Deep Q-network
Scalability	Small or Medium sized network	Extremely large sized Network
Computational time	Increased as the network size increases	Suitable for large networks
Q-function approximator	Mostly regression models	Mostly DNN like CNN, RNN, LSTM, MLP, etc.
Experience replay	Not applicable	Transition state buffer to store previous experiences
Solution methods	Tabular method or policy-gradient methods	Neural network and actor-critic method for value-function approximation

E. Classification of DRL Algorithm in Energy Market

Most of the DRL algorithms fall into two categories, model-based and model-free. Model-based are influenced by control theory, while model-free is devoid from the strong mathematical computations. Model-free has the advantage of being fast and efficient, whereas, model-based are more complex than model-free. Most policy-based and value-based problems are model-free [24] and are widely used in several applications especially the energy market. Policy-based is used to learn the best policy for the best action to maximise reward, while value-based is to find the optimal value function. The DRL algorithm classification is summarised in Fig. 5. In the following, we review the literature on the use of DRL in energy market based on the set objectives including utility improvement, profits, and system costs.

1) Utility Improvement: Energy generation and demand flexibility are mostly achieved by some forms of ESS through the provision of services over multiple times-of-use within the electricity market. In [15], an energy trading framework among MGs is formulated based on the predicted energy profile of the MG, i.e, battery level, consumption, generation capacity, and energy trading history. This study further improved the utility of the MG by proposing a deep Q-network (DQN) that exploits the CNN to estimate the Q-value. Optimal strategies for MGs using DRL algorithm was modelled in [41] in the local energy market, whilst also considering the physical constraints of the MGs. Specifically a DQN algorithm is utilised for the MG to maximise their utilities. An energy trading game is proposed in [73], where prosumers decide its trading strategy according to its energy generation capacity, battery levels, consumption, and trading history. For dynamic trading scenario, a Q-learning strategy is further proposed. Such approach provides an optimal strategy that does not depend on knowledge of the future consumption and energy capacity of other prosumers in the market. To accelerate the convergence speed, a hotbooting technique is used to exploit the energy trading experience to accelerate the learning process.

2) Prosumers' Benefit/Profit: In the current electricity market, prosumers have limited options of energy services to choose from. To enable the market provide more choices to consumers, different market mechanisms have recently been proposed in the literature. These include peer-to-peer model [16], [63], [74] community energy trading [75], [76], and prosumer-grid integration [77]. In the energy market, the intraday market trading is modelled as a continuous process and solved explicitly, where MG agents learn an optimal trading policy instead of selecting the price to sell or buy energy, which does not give maximum profit. Indirect customer-to-customer energy trading in a localised event-driven market is proposed in [78], which is solved using RL for customer's benefit maximisation. The authors of [42] presented a prosumer trading behaviour in a local energy market utilising DRL. In controlling ESS in real-time electricity market under price uncertainty, study [38] developed a DRL technique for a stochastic control policy to map information processed by RNN to ESS charging/discharging actions. Specifically, the filtered information is extracted using an exponential moving average and RNN, solving the optimal policy by using the proximal policy optimisation algorithm. In optimising profits over the trading horizon, study [39] solves the real-time bidding strategy of a MG utilising RL. A joint bidding and pricing strategy was modelled in [40] using deep deterministic policy gradient (DDPG) algorithm to determine the optimal bidding and pricing policy in an wholesale electricity market. Deep-Q learning with experience replay mechanism was proposed in [42] to promote prosumers' willingness to participate in localised energy ecosystem thereby improving their benefits.

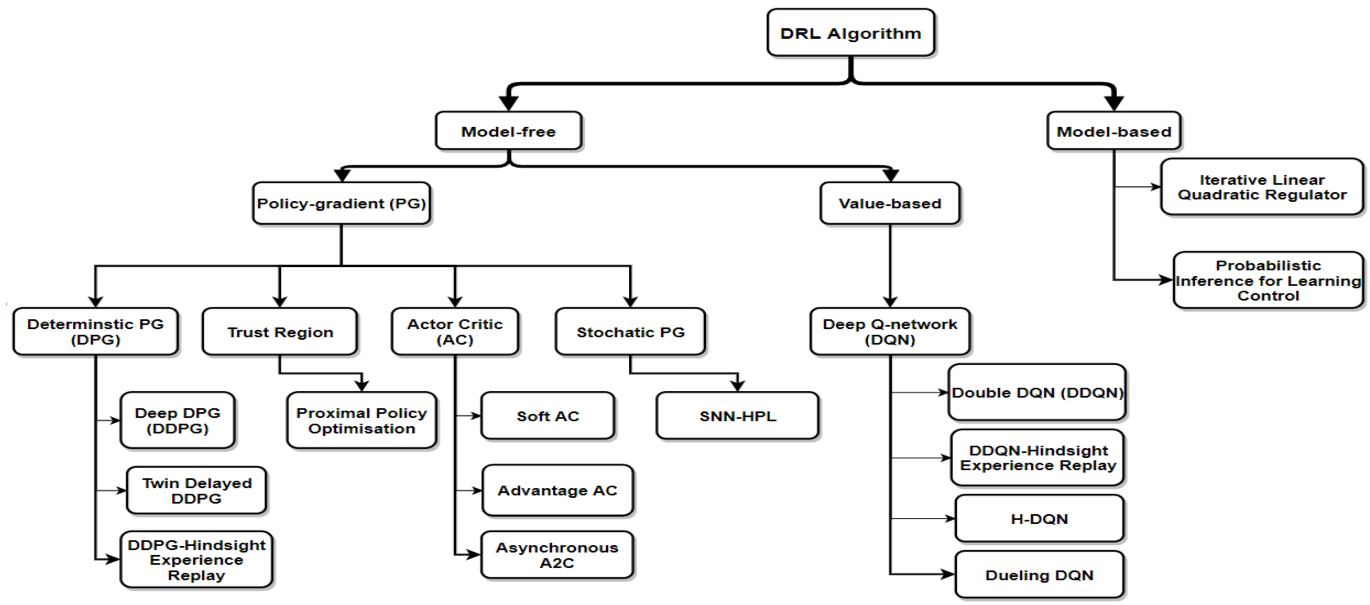

Fig. 5. DRL classification

3) System Costs: In reducing the electricity costs, a fitted Q-iteration (batch RL) to address uncertainty in providing flexibility due to lack of knowledge of future demands and solar PV generation in a multi-carrier energy system was proposed in [9]. The flexibility is provided by controlling the operation modes of a battery using RL. A dynamic pricing and energy consumption scheduling problem between the service provider, utility company, and customer is studied in [79]. RL algorithms are developed for the service providers and the consumer for strategy learning with limited information. This helps to reduce system costs due to the learning capability of the algorithm.

A summary of the reviewed articles based on RL/DRL usage in the energy market and flexibility provision is presented in Table VI, highlighting their objectives and learning algorithms.

4) Inferences from the Reviewed DRL Articles: From articles [9], [15], [38]–[42], [79], we note that the model-free based DRL is widely applied, especially the value-based approach involving the DQN algorithms. The rationale for the choice could be because of its high accuracy rate as well as the high speed achieved during model training [80]. So far, a few research explored the policy-gradient based methods for energy market applications. The study of DRL techniques for load forecasting presented in study [22] compares popular policy gradient algorithms including DDPG, recurrent-DPG (RDPG), and asynchronous advantage actor critic (A3C). The study concludes that prediction accuracy and convergence speed of DDPG and RDPG outperforms the A3C model but requires a significant amount of state transition samples resulting in higher computational time in model training. DRL is an improvement over RL by using the DQN with experience replay, recent advances in AI have enabled an added advantage by utilising DDQN or dueling DDQN which is yet to be applied in the energy market. For instance, study [15] has shown that utilising hotbooting techniques with Q-learning improves MG utility by 22.3% relative to DQN. This established that, while DQN is mostly used, other learning algorithms have the potential for better result and their potentials should be explored for energy market applications.

TABLE VI
SUMMARY OF THE REVIEWED DRL PAPERS TO ENERGY MARKET

REF	Objectives	Physical Constraints	Learning Algorithm	Simulation Period
[41]	Utility improvement	Yes	DQN	1 year
[42]	Prosumers' benefits	N/A	DQN/DNN	3 years
[73]	Utility improvement	N/A	Hotbooting Q-learning	N/A
[79]	System cost	N/A	Q-learning	N/A
[40]	Prosumers' profit	N/A	DDPG/DNN	30 days
[9]	Electricity cost	N/A	Fitted Q-iteration	24 hrs
[15]	Utility improvement	N/A	DQN/CNN	24 hrs
[38]	Total profit	N/A	PPO/RNN	1 yr
[39]	Trading profit	N/A	DQN/DNN	2 hrs

IV. BLOCKCHAIN DISTRIBUTED CONSENSUS ALGORITHM

Different types of distributed consensus algorithms are actively being developed and used in different applications. These algorithms determine the scalability, transaction time, integrity, consistency, and efficiency of the BC solutions [18], [44]. Broadly speaking, every BC process involves the creation of block signifying the beginning of a transaction, then the created block is accepted by the BC members. This process is called *reaching a consensus*. After a consensus is reached, the newly created block remains digitally immutable and it is cryptographically attached to the chains in the BC [46]. Reaching a consensus in a widely distributed system is challenging, as the consensus algorithms would need to be resilient to attack, node failures, processing delays, corrupt messages, etc. These has resulted in the proposal of several CAs, each with its trade-offs. The next subsection presents the popular CAs and their suitability to integrate with AI-based applications in ETS.

A. Proof of Work (PoW)

PoW is the pioneer consensus algorithm where at least 51% of the nodes compete to solve a complex mathematical problem (cryptographical puzzle of generating hash output) to validate the transaction for a reward. PoW is mostly used by Ethereum and Bitcoin [81], [82] platforms. The validated transaction is then permanently added to the BC. Solving the cryptographical problem is based on trial and error method, which most times results in increased consumption of computing powers in order of 47.1 Terawatt an hour [83] and high delays in transaction approvals. With AI applications characterised by voluminous real-time data with high velocity, variety, and veracity, to handle real-time data streaming, anomaly detection and real-time decision making, PoW with high delays could be a barrier to its integration in energy network.

B. Proof of Stake (PoS)

In solving the high energy consumption challenge of PoW, the PoS is created to assign the process of creating new blocks to a set of validators [84]. The validators could be randomly selected or delegated. Although the energy consumption is reduced as a result of the validators, the delay problem may still prove to be a challenge for its use with AI applications. This is because the validators may choose to delay processing transactions, decided not to participate in the validation, or are malicious nodes themselves [32]. Variants of PoS includes delegated PoS and leased PoS.

C. Byzantine Fault Tolerance (BFT)

BFT algorithm originated from the work on Byzantine fault [85], where a set of nodes agree on a joint plan of action, for instance, to validate a transaction. BFT implementation considers that some nodes in the network are compromised, thus the challenge is for the set of nodes approving transactions to ensure their messages are delivered devoid of the malicious nodes. According to Lamport et al. [85], consensus on the transaction is guaranteed if the number of malicious nodes is less than $1/3$ of the network nodes. BFT is mostly used in critical systems especially in sensitive environments such as airplane engine systems, and nuclear systems and could be considered suitable for AI applications. When a significant amount of digital signatures approving a transaction is collected, the consensus is reached and the transaction is considered valid [18]. However, as the size of the network increases, the message overhead increases which could result in transaction delay, scalability, and higher memory requirements [44]. Variant of BFT includes practical BFT and delegated BFT.

D. Proof of Authority (PoA)

Like BFT, PoA delegates some specific nodes in the network with authoritative control to form a consensus based on majority votes in validating a transaction. This authority could be an entity, such as an operator in the energy network, holding a special key for approving all transactions. PoA solves both the high energy consumption of PoW and the problem of dependency of PoS, but it is better suited for private BC implementation and may be prone to single point of failure. However, in such cases, the security vulnerabilities of private BC still applies, where validators are prone to attack, and the validators could also be sources of attacks. For AI applications in the energy market, PoA can be specifically useful in practical implementation of grid-connected DERs with the distribution network operator serving as the authority or regulatory body.

E. Proof of Burn (PoB)

PoB involves validators spending/burning their coins to create a new block and get rewarded [90]. By so doing, the validators improve their stake in the network, and the coin burning process reduces the number of coins in the network as well as increases the value of the coins. However, that could result in unnecessary waste of resources [18]. By implementing a resource management scheme, spending could be reduced in the network. In scenarios designed to incentivise prosumers to participate in grid balancing, PoB can be applied to burn learning models and search trees to maintain the value across the BC [32].

F. Proof of Elapsed Time (PoET)

Like PoA, PoET selects a leader to create new blocks in the chain by associating response time with a timer and selecting the node with minimum expiry time as the leader [93]. The leader selection algorithm is continuously executed all the time. This process may also help in detecting malicious nodes in the network, especially when a particular leader is constantly selected or has the same minimum expiry time all the time. It is quite energy-efficient and can scale to thousands of nodes. PoET could find applications in AI system with delay-tolerant applications, such as off-line system since the AI applications need to wait until the expiry of the timer, which could slow down data processing.

G. Proof of Capacity (PoC)

PoC is also called proof of space or proof of storage, which works as an alternative to PoW, by storing all possible nonce values on the nodes' hard drive. Thus instead of finding a random nonce as in PoW to unlock a block, it searches for a matching nonce-hash pair in its hard drive to unlock the

TABLE VII
COMPARISON OF BLOCKCHAIN CONSENSUS ALGORITHM FOR ENERGY MARKET

Features	PoW	PoS	PoA	PoB	BFT-based	PoET	PoC	PoI	PoAc
Blockchain type	Public	Either	Private	Either	Private	Either	Public	Private	Private
Platform	Ethereum	Ethereum	Ethereum	-	Hyperledger Fabric/ Tendermint	Hyperledger Sawtooth	-	-	-
Transaction rate	Low	Medium	Medium	Medium	Medium	Medium	-	-	Medium
Scalability	Medium	Medium	Medium	Low	Medium	Medium	Medium		Medium
Energy savings	No	Yes	Partial	Yes	Yes	Yes	Partial	Yes	Partial
Example	Bitcoin, Ethereum	Peercoin	Parity, Geth	SlimCoin	Hyperledger Fabric	-	BurstCoin, SpaceMint	-	Espers
Pros	Well established	saves energy	saves energy	Improved security	Improved trust	Improved security, consumes less energy, scales well	Saves energy	Saves energy	Efficient storage, security and network communication
Cons	Consumes energy	Vulnerable to attack	single point of failure, vulnerable to attack	Partly based on PoW, thus consumes some energy	Increase in message overhead as the size of the network increases	Leader selection waste time	Vulnerable to attack	Vulnerable to attack	Partly based on PoW, thus consumes some energy
Reference	[30], [86]–[88]	[68]	[29], [89]	[90]	[91], [92]	[93]	[94]	-	-
Trust model	Low	Low	Medium	Medium	High	Medium	Medium	Medium	Medium
Suitability for AI	No	Maybe	Maybe	Maybe	Yes	Maybe	Maybe	Maybe	Yes

block. Network nodes with higher disk space running a PoC algorithm have the advantages of holding a higher stake in the BC network [32].

H. Proof of Importance (PoI)

PoI is similar to PoA, where validating nodes are selected based on their stake in the network. Here, the stake is based on successful past validations. The validators are ranked based on their frequency of successful validations. Based on the ranks, importance is attached to the validators, and their approved transactions out-weighs other validators in the network [32]. This increases trust in the network and can be suitable for AI applications in energy market.

I. Proof of Activity (PoAc)

PoAc is a federated protocol of PoW and PoS, combining its advantages and disadvantages. Here, block validation is finalised when signatures are received from randomly selected nodes with a higher stake in the network. It initially starts with an empty BC, where validations are first based on PoW for validators to receive rewards to increase their stake in the network. Then the algorithm enables PoS for validators with an acceptable stake in the network. PoAc is particularly efficient for providing storage, security, and network communication [32], which is well suited for off-line AI applications for the energy market requiring less data availability with high security of content.

J. Classification of Consensus Algorithms in Energy Market

In the energy market, third parties like brokers, trading agents are usually used as intermediaries for transaction management creating a complex system with increased cost delayed transaction processing and communications [18]. DLT and smart contract allow direct interaction between energy trading entities devoid of intermediaries. Based on a consumers' consumption pattern, energy deals on the market place can be searched and ordered against a particular delivery period, while transactions are securely recorded in the BC, and payments processed based on the smart contract [46]. BC in energy network has seen an increase in its application ranging from energy trading, to demand response to grid resilience. Specifically in the energy market, an architecture for BC-based P2P energy trading was proposed in [95].

Utilising the Bitcoin BC, i.e. PoW, study [88] proposed an energy trading framework based on private messaging and multiple signatures. Practical implementation of PoW is found in [30], [86], [87]. Utilising a consortium BC running a consensus algorithm such as PoS or BFT, where a set of peers acts to approve transactions was proposed in [96] to achieve demand response in balancing electricity supply and demand through incentive provisions. The consortium BC was proposed to address security and privacy challenges during energy transactions. Likewise, [97] investigated a consortium BC to address the security challenges resulted from untrusted and nontransparent energy market transactions. A practical implementation of PoS is in [68], while [98] described a practical implementation of a PBFT consensus algorithm.

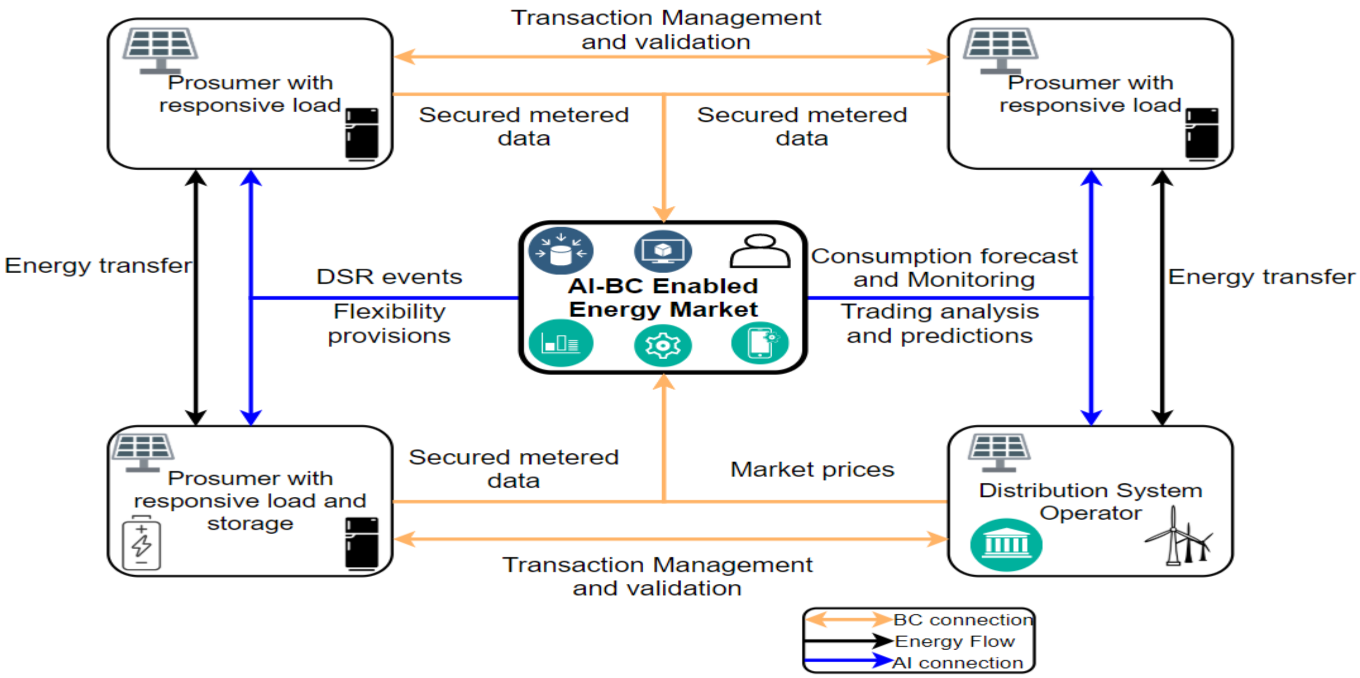

Fig. 6. An AI-BC enabled energy market

With other CAs, a BC platform was developed in [94] that enables bilateral transactions between consumers and renewable producers using PoC to reduce energy costs. Recently, study [36] proposed a proof of energy consensus protocol for energy trading. Table VII summarises other proofs of X use cases.

1) Inferences from the Reviewed Articles: From the reviewed articles, the PoW algorithm is widely applicable in energy network, for instance, a survey of 140 BC initiatives in energy sector presented in [18] shows that 53% of the articles utilised PoW as their CA. However, due to its high energy consumption property, PoW is not suitable for AI-based applications. PoS has been implemented to reduce the energy consumption of PoW, as such several other proofs of X algorithms evolved from PoS, e.g. BFT, while some are hybrid of PoW and PoS, e.g. PoAc. Although PoW, PoS, and BFT are mostly used CA in energy network, these algorithms have their tradeoffs as highlighted in Table VII. It is therefore recommended that other proofs of X algorithms yet to be tested in ETS be further explored. Furthermore, most of these algorithms consider the network and middleware layers of the BC system. This opens opportunities for researchers to explore application-specific consensus algorithms designed to explore the learning capabilities of AI algorithms.

V. Proposed AI-BC Framework for Energy Market

The previous sections discussed the models of DRL and BC CAs and their applications in energy market. In this section, we present a framework and summarise the open challenges for integrating the two technologies for energy network. A proposed joint AI-BC framework is presented in Fig. 6,

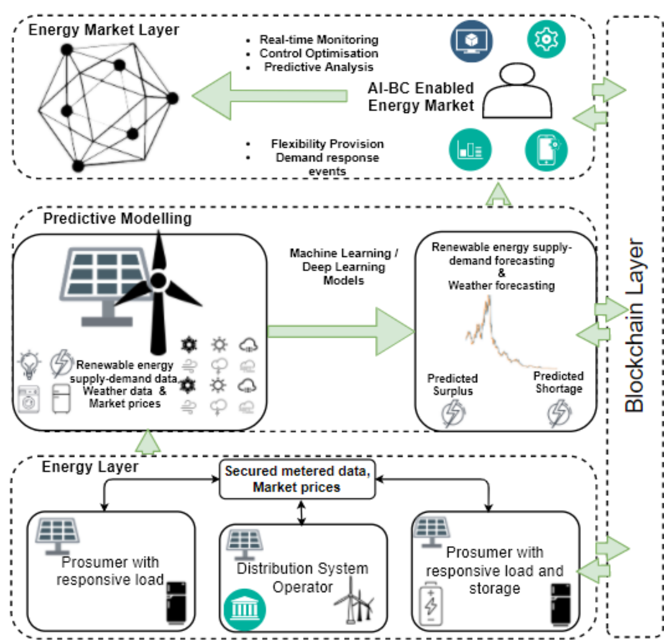

Fig. 7. An Hierarchical Architectural of AI-BC enabled energy market Framework.

For clarity, the framework is re-presented in a hierarchical architecture of Fig. 7 with four layers: 1) Energy data layer, 2) Prediction modelling layer, 3) Energy market layer, and 4) BC layer. The layers are discussed in the following.

1) Energy data Layer: This layer refers to energy data gathered from different sources e.g. consumption sources including connected sensors, home appliances, home energy management systems, and smart meters; generating sources including solar PV panels, wind turbine, and energy storage systems; energy prices and preferences. These data are securely stored and exchanged via the BC layer to the appropriate end entity for further processing.

2) Predictive Modelling Layer: The AI-BC enable market platform act as a federated power plant (FPP) that utilises the transmitted energy data for real-time monitoring of the connected assets. The collected data from energy data layer is pre-processed on this layer. This involves processes like data cleaning, data integration, data transformation and data reduction to remove noise and transform the data into usable format for better prediction results. The pre-processed data is further classified according to the type of prosumer, either a residential user or a SME, as well as type of data, either a demand, generation, or price. The platform uses AI predictive modelling like RDPG to predict the values of all estimates over a period utilising the classified data. The predicted values include the consumption, generation and price forecast. The forecast result is then stored on the BC for security purposes. Besides, the FPP platform only takes in data and provides an intelligent interface for the varied prosumers on the platform including the SMEs and the electricity markets (the wholesale market and flexibility services), maximising the economic returns. In addition, it provides optimisation control and real-time services such as DSR, user preference, flexibility provisioning, improved comfort and efficiency for the connected prosumers.

3) Energy Market Layer: For energy trading relations among the participants on the platform, the BC module securely transmits the market prices from the distribution service operator to the AI platform. The platform uses these price signals and the consumption patterns of the prosumers to optimised trading decision on the best price and time to buy, sell, or store energy for maximum investment return and cost reductions. By responding to the market signals, local balancing, and lower energy prices than grid offering would be achieved.

4) Blockchain Layer: Since BC maintains trust, security and privacy of data and transaction among the prosumers, it is considered as a cross layer entity. For instance, the energy generation and consumption data from the energy data layer is securely stored on the BC layer as well as transmitted through the BC layer to the prediction modelling layer. Similarly, the data from the prediction modelling layer and energy market layer are stored on the BC layer and securely transmitted appropriately. The BC layer validates and manages the transactions between the trading entities. Energy trade validation and transaction management processes involves requests to buy or sell energy, generation of smart contracts and certificates for transactions, and exchanges of offers and payments. After an agreement to trade energy is reached and a smart contract is created, the transaction is approved using a PoA algorithm which seems more specifically suited and potentially implementable for the energy trading. This triggers the energy exchange process through the connected smart meters and subsequently, payment exchange between the trading partners is ensured.

A. Discussion on Future Research Direction on AI-BC Technologies for Energy Market

This section first discusses each technology's future research direction before proceeding to discuss the inherent challenges in each technology that need to be addressed prior to integration. This is closely followed by joint challenges in both technologies.

The choice of distributed CA in BC implementation is an evolving area of research. However, from the literature review, the benefits of CAs in ETS outweighs their disadvantages in terms of efficiency and cost. For instance, Ethereum- the most widely used BC platform, is based on PoW, which is slow and energy-intensive due to the block verification and validation [18]. This resulted in the move towards a more energy-efficient, faster, and more scalable distributed consensus algorithm. IOTA and "sharding" enable DAG and parallel processing respectively [26], with decentralisation and security as the trade-offs.

Furthermore, the initial cost of BC deployment is higher than the traditional transactional methods such as relational databases, but with better security and privacy enhancements. Thus, BC on its own requires further research on how to tweak and adapt it in AI applications to maximise its performance when integrated.

On the other hand, new techniques are required to significantly reduce the training time and improve convergence of DRL algorithms. Whereas the learning capability of the DRL algorithm requires an agent to be deployed, energy market is essentially a multi-agent environment with many actors such as energy sources (CHP, wind turbine, solar PV), system operators and other services providers. Hence, further research is required to extend DRL to multi-agent system in order to be more amenable to ETS.

Another potential area is to investigate better reward functions that allow agents to properly learn and optimise interactions in the environment, incorporating risk management in the decision making process and constructing bids and prices with a profit guarantee.

In addition, most of the research papers on RL for the energy market neglect the effect of critical physical network constraints. This is important as the transmission losses and power limit capacity at some nodes could affect the optimal decision making or strategy of a prosumer.

The parallel open research challenges of integrating AI and BC technologies to the energy network are as follows.

- **Privacy and Data Access:** In the public BC ledgers, data are distributed and available on all the nodes on the network. This is a privacy concern. Moreover, the use of IoT devices like smart meters collects additional personal information which may also be stored on the BC platform, resulting in additional vulnerability. Although the use of private BC allows authorised access to particular information, this restricts the access to data

by AI platform in performing analytics for informed decision making. Thus, research in data access between AI and BC platform (either private, public, or consortium) whilst ensuring confidentiality and privacy of data is highly recommended. Interestingly, combined AI-BC can enable anonymous data detection and secured data sharing among prosumers. But this possibility requires more research validity into data authorisation process for different prosumers.
- **Scalability and Accuracy:** The potential number of transactions processed using the public BC platform is limited due to the time required for confirmation. This makes scalability a major concern with BC platforms. For instance, with the increasing DER integration and connected devices (loads, generating units, metering devices, etc.), transactions are meant to be processed in order of millions to deter double payment and delay. Delayed transactions would impact on the training and accuracy of predictive ability of AI models affecting the joint integration with BC for the energy market. However, with a distributed ledger like IOTA platform, where the ledger is built on DAG and not linear blocks, this features scales up transaction numbers and times [99], [100]. DAG is an emerging technology as BC, and its integration with AI has not received much attention in the energy research community. Thus more research is needed in adopting DAG fully with AI in energy market applications.
- **Security and Suitability:** Ethereum is the mostly deployed BC platform in energy market. However, it faces several security challenges and vulnerabilities to cyber-attacks. Ethereum has been the target of serious attacks in the past and resilience to such attacks is important, especially for critical applications like the energy trading [32]. In particular, the consensus algorithm is implemented by miners in the network which can be compromised. The use of trusted nodes in private BC as Hyperledger is less vulnerable compared to public BC, but this has found limited interest in the energy market. To ensure its suitability for AI integration, additional trust and security layer is needed to ensure security, privacy, and access to data for AI implementation. Although privacy and security provided by BC platform for managing energy transactions is tighter than the traditional database system, BC security is still an open challenge.
- **Lack of standards, interoperability, and regulations:** Regulatory activities are by several standardisation bodies including IEEE, NIST, and ITU [32], looking at resolving these very important issues. As such, there is no devised BC standard yet. Similarly standardisation of big data development in smart grid including inteoprability of various devices is still in development. Integrating AI with BC in the energy market, therefore calls for open research in devising efficient universal models and proofs of concept for integrating the two technologies. This should be followed by definition of appropriate technical standards, interoperability requirements and guidelines for harnessing the potentials of the two technologies. For instance, in the energy market, a new contract is required to describe agreements between prosumers especially when the use of the public grid is involved. Thus the need to integrate the energy markets into the current regulatory practices.
- **Lack of Acceptance:** The complexity and lack of long term use as well as the experience with BC resulted in associated risks of its usage in the energy network. While theoretical works and field trials are proving its applicability and efficiency in the energy network, it's integration with the existing distribution network raises some major concerns for network operators. For instance, questions such as how BC fits into the existing distribution network? does BC provide incentive or charge for DSO to allow energy transactions through their network? what is the effect of the charge on the overall cost and carbon reduction?. Further investigation is therefore required to address these concerns.
- **Cross-domain Research:** Presently, the modes of operation of BC and AI are independent, which makes parallel process communication difficult. This barrier can potentially jeopardise performance-related metrics of integrating both technologies. Although, as highlighted from the comparative review of Section II-D that recent effort are investigating their joint applications as presented in [31], more cross-domain based research for the two technologies is highly needed in reaping the benefits of both technologies in energy network.
- **Selection of appropriate Technique:** As can be seen from the DRL classification of Fig. 5 and Table VII that several DRL and CA exists, selection of appropriate technique for AI-BC based application may cause performance bottleneck if the selected technique is not optimal or near-optimal. Since the techniques are not one size fit all, future research work would need to focus on developing specific DRL and CA techniques that considers all the variability and dynamics of the energy market for optimal performance metric.

VI. Conclusion

Integration of AI with BC in ETS is faced with many challenges ranging from data control, privacy, transaction delays and management complexities. In this paper, we reviewed recent works in AI and BC with respect to ETS and analyse working principles, existing models and the barriers to AI-BC integration in energy market applications. We carried out detailed comparative analyses of CA and DRL algorithms and found that although some progress has been recorded in exploiting both technologies individually, the overall outcome was mostly sub-optimal performance due to the weaknesses and trade-offs inherent in each of them. Hence, we discuss the benefits of integrating AI and BC in ETS and proposed a new framework for exploiting both technologies in an integrated manner. Finally, we enumerated the future research areas in each technology that can improve adoption in ETS.

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