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SURVEY

Energy Routing Protocols for Energy Internet: A Review on Multi-Agent Systems, Metaheuristics, and Artificial Intelligence Approaches

AMANI FAWAZ[1], (Graduate Student Member, IEEE), IMAD MOUGHARBEL[2], (Member, IEEE), KAMAL AL-HADDAD[2], (Life Fellow, IEEE), AND HADI Y. KANAAN[1,2], (Senior Member, IEEE)

[1]Department of Doctoral Studies, Faculty of Engineering, Saint Joseph University of Beirut, Beirut 1104 2020, Lebanon
[2]Department of Electrical Engineering, École de Technologie Supérieure, Montreal, QC H3C 1K3, Canada

Corresponding author: Amani Fawaz (amani.b.fawaz@live.com)

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ABSTRACT The Energy Internet (EI) is transforming power networks by integrating Smart Grids (SGs), Distributed Energy Sources (DESs), and advanced communication and data technologies. This transformation increases complexity, as energy transmission evolves into a multi-source, multi-path, and multi-load system, with Peer-to-Peer (P2P) energy trading markets and Energy Routers as central drivers. As power networks grow and become more decentralized, the need for efficient and adaptive power routing protocols has become crucial to ensure their reliable and scalable management. This review focuses on energy routing strategies using multi-Agent architectures, Artificial Intelligence, and Metaheuristic optimization techniques. These approaches are well-suited to support the transformation of power networks into more distributed, dynamic, and complex systems. Spanning research from 2018 to 2024, this paper consolidates diverse studies, filling a critical gap by providing a comprehensive overview of power routing solutions for the evolving EI. It highlights key methodologies, limitations, and future research directions, offering a valuable reference for researchers.

INDEX TERMS Artificial intelligence, energy internet, energy routing protocols, metaheuristic, multi agent systems, smart grid.

GLOSSARY OF TERMS

Terms	Definitions
Energy Internet (EI)	Refers to the next-generation smart energy network that integrates distributed energy resources and intelligent power management systems. It enables decentralized, efficient, and autonomous energy trading. EI shares similarities with the traditional Internet but focuses on energy routing rather than data transmission.
Energy Router (ER)	As a key component of the EI, it provides a power electronic interface for information-driven energy control, enabling energy routing, precise energy flow regulation, and power quality management.
Multi Agent (MA) System	A collection of two or more intelligent agents that work together to solve problems in a distributed manner.

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I. INTRODUCTION

The Energy Internet (EI) is a newly invented concept that supports Peer to Peer (P2P) energy trading and provides highly efficient energy distribution. In [1], the EI is defined as "An implementation of smart grids where energy flows from suppliers to customers like data packets do, over the Internet". The authors consider EI advantageous due to its openness, robustness, and reliability. The term EI [2] is widely used in the United States and China; however, researchers globally have recognized similar concepts under different names. In Japan, it is referred to as the digital grid. The Digital Grid in Japan [3] is a fully decentralized energy system that enables P2P energy transactions while enhancing grid stability and supporting new on-demand energy markets. Digital Grid Routers enable direct energy transfers between points, like data packets on the internet. This innovation transforms energy distribution and market dynamics, allowing more efficient and flexible power routing. The EI architecture [2] consists of seven layers (FIGURE 1), inspired by the Open Systems Interconnection model (OSI). The Physical Layer serves as the foundation, consisting of energy cells. The Energy Link Layer enables P2P energy trading within an Energy Intranet, while the Network Layer manages the physical connections between energy cells, where Energy Routers (ERs) play a key role in establishing and maintaining these links. The Transmission Layer facilitates power exchange between different Energy Intranets, and the Consumption Layer regulates energy usage within energy cells. The Communication Layer ensures seamless interaction among devices, entities, and stakeholders, while the Business Layer oversees financial transactions.

Recently, the authors, in [4], redefined the EI as a transformative system consisting of three layers: the physical layer, information layer, and value layer. The Physical Layer connects various energy sources, including electricity, heat, cooling, and gas, enabling energy sharing and demand response through distributed energy resources (DERs). The Information Layer gathers data from the physical layer, enabling real-time coordination and decentralized energy management. The Value Layer leverages this data to create new business models.

In [5], the proposed EI model introduces a decentralized approach to energy exchange, allowing resources to trade energy independently of a centralized operator while ensuring system stability through an Energy Internet Service Provider (Energy ISP). The Energy ISP ensures secure and reliable energy transactions by implementing dynamic quantity limits on exchanges and managing centralized resources when necessary. Structurally, the EI is designed to mirror traditional Internet protocols, incorporating elements such as Energy Internet Cards (analogous to MAC addresses) and Energy IP addresses for network identification and mobility tracking. Additionally, an energy-specific Transport Layer protocol ensures the reliable transmission of energy data, while an Application Layer facilitates standardized communication for energy exchanges.

ERs play a crucial role within the EI by enabling energy routing between geographically dispersed resources. These devices manage power dispatch, information exchange, and transmission scheduling, thus supporting a dynamic grid structure. The introduction of ERs is central to managing power flow across interconnected lines, making them essential for maintaining the stability and efficiency of this evolving grid. The structure of the ER consists of input/output ports to connect energy sources, loads, other ERs, a power exchange structure formed by converters, and a controller. Various architectures for ERs exist in the literature. FIGURE 2 illustrates a general ER architecture.

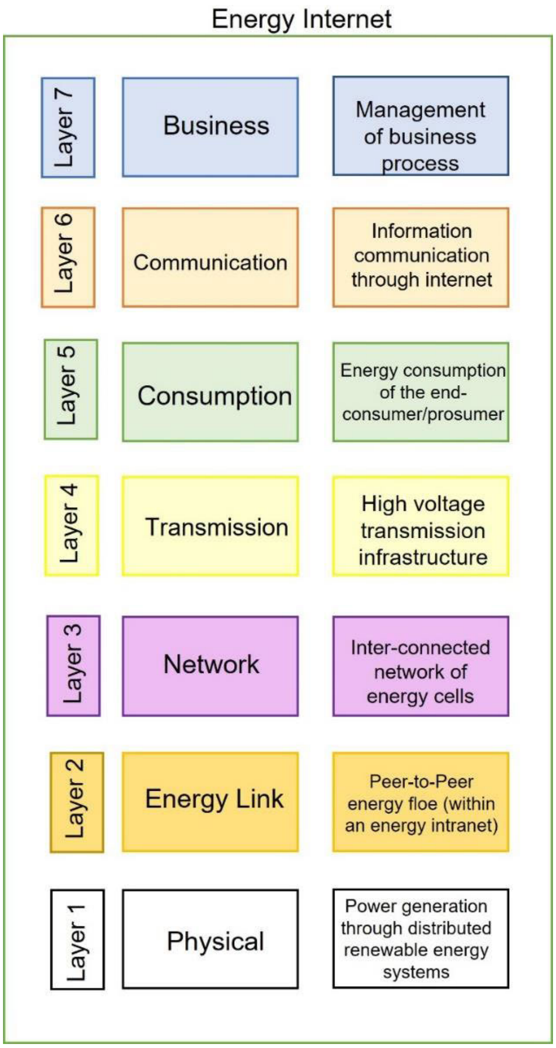

FIGURE 1. Energy internet architecture.

Microgrids (MGs) are essential within this system, as they integrate energy sources, storage, communication networks, and intelligent devices to optimize power flow within the grid. With the evolution of network architecture, energy routing needs upgraded ERs to support bidirectional power flows and efficiently perform energy routing functions. Energy routing problems are addressed by matching producers with consumers (subscriber matching), preventing congestion and failures (transmission scheduling), and identifying efficient transmission paths. ERs should be associated with an appropriate routing algorithm to deliver energy from the source to a specific destination. Optimizing energy routing minimizes transmission losses, maximizing energy delivery while reducing greenhouse gas emissions and dependence on fossil fuels. Efficient energy routing supports renewable energy integration by optimizing electricity flow, reducing fluctuations, and enhancing grid reliability. Energy routing protocols support P2P energy trading and decentralized energy markets. They encourage cleaner energy use and decrease reliance on fossil-fuel-based power plants.

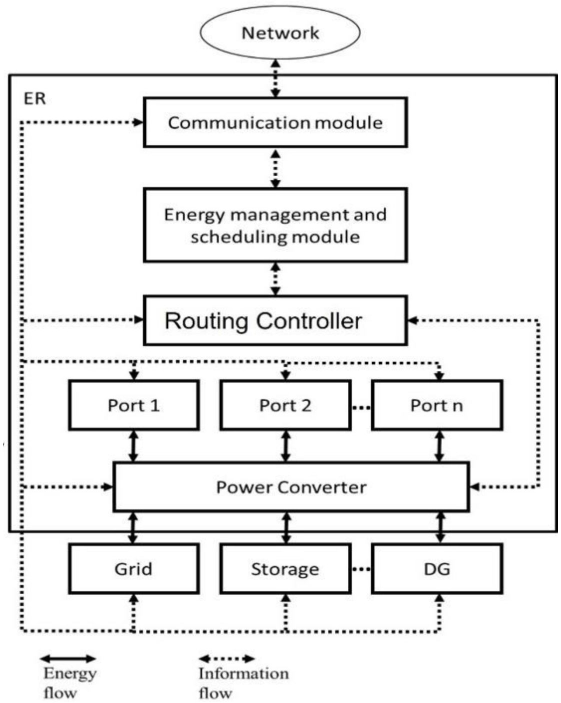

FIGURE 2. General architecture of the ER.

The motivation for this review paper stems from the gap in the existing literature, where previous reviews [6], [7], [8], [9], [10] on power routing protocols fail to sufficiently categorize existing methods based on their characteristics and functions. These reviews often lack detailed comparative analysis and clear future directions to guide researchers in the field. Moreover, they do not adequately address all the methodologies and categories used to solve power routing problems, which limits the development of new and efficient strategies. Power routing in energy networks is a rapidly evolving and promising domain with numerous challenges, including dynamic energy distribution, security concerns, and computational efficiency. Therefore, a comprehensive evaluation of energy routing protocols is necessary to identify their strengths, limitations, and suitability for different network conditions. This paper aims to fill this gap by providing an in-depth analysis of energy routing protocols based on Multi-Agent (MA) architecture, Artificial Intelligence (AI) computation, and metaheuristic optimization.

The key contributions of this paper lie in its comprehensive review of energy routing protocols, focusing on the integration of metaheuristics, AI, and MAS to optimize power distribution in decentralized power grids. By categorizing existing methods, this paper highlights the strengths and weaknesses of each approach, emphasizing how metaheuristic algorithms minimize energy losses, AI improves system performance through predictive routing, and MAS promotes decentralized decision-making. The integration of these strategies is proposed as a framework to optimize energy routing in dynamic and renewable energy networks.

Additionally, the paper outlines the importance of addressing key issues such as energy loss minimization, scalability, renewable energy integration, and adaptability to fluctuating demands. Future research directions are identified to enhance the efficiency and sustainability of energy routing systems, fostering further exploration in this promising domain. Ultimately, this paper provides a foundation for developing more effective energy routing solutions, contributing to the optimization of energy flow in smart, decentralized energy networks.

The remainder of this paper is organized as follows: Section II introduces the energy routing problem in the EI-based Networks; Section III discusses the key characteristics to consider when implementing power routing protocols; Section IV presents existing energy routing protocols based on MA architecture, AI computation, and metaheuristic optimization; Section 0 provides a comparative analysis of these approaches and discusses future directions in power routing within the EI. Finally, Section VI concludes the paper.

II. POWER ROUTING PROBLEM IN EI-BASED NETWORK

The power network, composed of multiple ERs [11], [12], [13], [14], [15], [16], [17], [18] is structured into two main layers: the Communication Layer and the Power Transmission Layer. The architecture of an ER [19], [20], [21], [22] remains largely consistent across most studies, with differences arising primarily in the design, implementation, and control strategies.

The power routing algorithm, integrated into the ER's routing controller (refer to FIGURE 2), dynamically determines the routing decisions based on data exchanged within the communication layer. Optimal Power Flow (OPF) and the power routing problem differ in their focus, scope, and objectives. OPF is primarily concerned with optimizing the operation of power systems by determining the power generated at each generator to minimize the cost of operating a transmission network. In contrast, the power routing problem focuses on dynamically directing electrical power through networks, particularly in decentralized systems with ERs, DERs, and P2P trading mechanisms. The objective of power routing is to achieve efficient, real-time energy distribution by selecting the optimal path for each source-load pair while minimizing transmission losses and supporting power constraints.

The EI model (see FIGURE 3) is characterized by a graph where ERs are the vertices, and power lines are the edges.

During power routing, the following constraints must be considered:

- The power losses of a path w_{path} (1) should be less than the transmitted power P_c, *path* is formed by several ERs to deliver a power packet from a source to a destination:

$$w_{\text{path}} < P_c \tag{1}$$

- The transmitted power P_c (2) should not exceed the maximum capacity of the path which is the minimum between the lowest interface capacity of $P_{ERs_{capacity}}$ and the lowest capacity of the power lines that constructed the path $P_{links_{capacity}}$:

$$P_c \leq \min\left(P_{\text{links } s_{\text{capacity}}}, P_{ERs_{\text{capacity}}}\right) \tag{2}$$

- The total power transmitted through a power line (3) should not exceed its available capacity $P_{(vi,v\,j)_c}$:

$$\sum P_{v_i,v_j} \leq P_{(vi,v\,j)_c} \tag{3}$$

- The total power flows into the same ER interface (4) should not exceed its capacity $P_{(vi)_C}$:

$$\sum P_{v_i} \leq P_{(vi)C} \tag{4}$$

One of the objective functions that have been used in different works [23], [24], [25], [26], [27], [28], [29], [30], [31], [32] to find the optimal path is minimizing power transmission losses *TL*. In DC lines, the total power loss in a power line that links two ER is related to the active power. Therefore, they depend on the resistance R_{ij}, the voltage V_{ij}, the pre-existing power P_{ij} in the line L_{ij}, and the transmitted power from producer to consumer P_c.

They are calculated using (5):

$$w_{ij} = \frac{R_{ij}}{v_{ij}^2}\left[\left(P_c + P_{ij}\right)^2 - P_{ij}^2\right] \tag{5}$$

On the other hand, the total power loss in an ER i (6) is related to the efficiency of electronic converters η_i:

$$w_i = (1 - \eta_i)\, P_c \tag{6}$$

Hence, the overall power loss of a transmission path between a producer and a consumer (7) is equal to the sum of power losses of all routers and power lines that compose this path.

$$TL = \underset{p\to c}{W_{path}} = \sum\nolimits_{i\in path} w_i + \sum\nolimits_{(i,j)\in path} W_{ij} \tag{7}$$

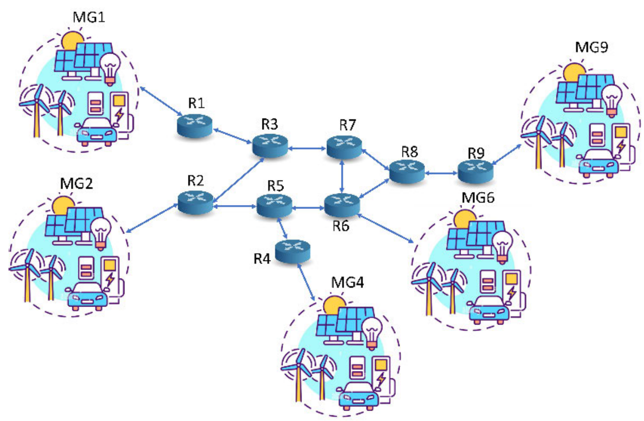

FIGURE 3. EI model formed by 9-ERs, (Ri) transferring energy between microgrids (MGi).

III. ENERGY ROUTING PROTOCOL CHARACTERISTICS

When designing an energy routing protocol, it is essential to consider the following characteristics:

- Energy routing schemes: Various strategies exist for power transmission, including centralized, distributed, and semi-centralized methods. Centralized routing aims to minimize transmission losses and meet network power limits but requires a central controller, impacting system reliability, privacy, and flexibility. Distributed routing allows users to choose their paths independently, reducing power losses but limiting global network optimization. Semi-centralized routing combines both approaches, using a central controller for power constraints and distributed algorithms for efficient paths, reducing computational load. Each method has trade-offs in terms of efficiency, control, and system characteristics.
- Algorithm complexity and computation time: The algorithm's complexity is assessed based on memory usage and execution time relative to the network size. These factors can vary based on network techniques and considerations. Some methods utilize specialized algorithms, increasing both complexity and computation time.
- Power routing constraints: They represent significant challenges for the EI and encompass limitations on energy supply, ER capabilities, and power link capacities. These constraints affect how energy is routed, especially in terms of avoiding overflows and ensuring security.
- Congestion management: It is a significant challenge in energy networks due to the rapid growth in power demand, leading to delays in energy delivery and increased network losses. It involves assessing the available capacity of power routing paths and considering factors like power level changes in links, which affect path selection due to increased link losses with higher transmitted power. Multi-packet routing becomes necessary because power link and ER capabilities limit the energy a single source or a single path can deliver, prompting some consumers to use multiple sources or multiple paths to meet their energy needs.
- Failure of ERs and links and topology changes: Routing algorithms must account for the dynamic behavior of

energy networks to adapt effectively to network failures and topology adjustments.

- Security: Ensuring security in power networks involves safeguarding data communicated to multiple users. Authentication, integrity, and confidentiality measures are crucial before transmitting power packets. Designing routing protocols for data networks introduces the challenge of protecting against severe attacks.
- Scenarios: The power routing protocol must account for various scenarios based on the number of energy sources available and the number of energy loads requesting power. These scenarios include multi-source multi-load (MSML), single-source single-load (SSSL), single-source multi-load (SSML), and multi-source single-load (MSSL).
- According to the literature, energy routing algorithms should address three primary functions:

1. Subscriber Matching (SM): Energy routing is demand-driven, so a power packet, source, and destination are not known in advance until a power demand from a load occurs. Additionally, the demander does not know from which supplier it will obtain the required energy. Consequently, a subscriber matching process is needed to facilitate P2P energy trade among all participants. The ER must accomplish this process after receiving the demand to determine which suppliers best satisfy the demander's requirements, such as delivery time, duration, power, and price. For some critical and heavy loads, more than one supplier is necessary to satisfy load demand. Therefore, one supplier can transmit energy to multiple consumers simultaneously, and consumers can receive energy from multiple suppliers at the same time. Subscriber matching can be executed in either one-to-one or one-to-many mode.
2. Energy-Efficient Path (EEP): Finding an energy-efficient path is critical for reducing power losses during energy packet transmission. The transmission loss is affected by several factors such as the voltage drop, congestion, energy conversion, router efficiency, and power link impedance. Even if the optimal path is discovered, it may not be an appropriate one if the ERs and links among that path do not support the transmitted power rate, type, and capacity of the transmitted energy. To prevent failures and overheating in the power system, such paths should be avoided.
3. Transmission Scheduling (TS): Transmission scheduling is a major operation for controlling and managing network congestion. In the context of EI, energy routing is determining the best transmission paths in response to the energy demand and sources availability. Without proper transmission scheduling, congestion could delay power delivery or cause system failures. Bidirectional power flow, voltage fluctuation, intermittent renewable energy sources, and the irregular and unstable variations in customers' energy demand increase the risk of congestion, leading to power network instability and failures in power components.

IV. REVIEW ON ENERGY ROUTING STRATEGIES IN EI

Many studies have investigated energy routing challenges to improve efficiency, proposing various routing algorithms. This exploration includes MA architecture, metaheuristics optimization, AI computation, as shown in FIGURE 4. Graph theory and game theory approaches will also be reviewed in separate publications.

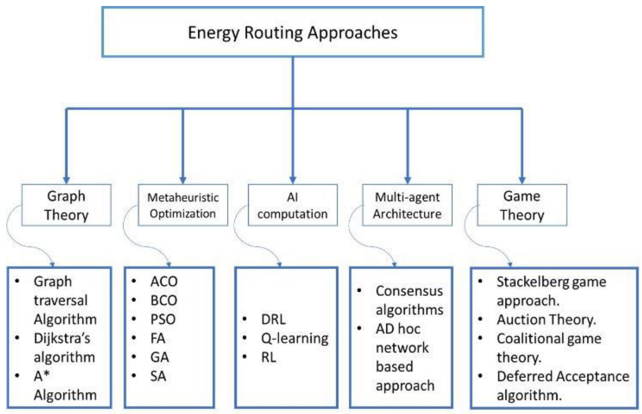

FIGURE 4. Classification of energy routing approaches.

A. MULTI-AGENT ARCHITECTURE IN POWER NETWORKS

MAS facilitates decentralized decision-making, enabling agents to dynamically manage energy flow, adjust routing paths, and allocate resources autonomously. This section reviews the applications of MAS in power networks, emphasizing its role in addressing energy management and routing challenges. It also examines how these solutions incorporate power routing characteristics from Sections II and III, with detailed insights into their approaches, advantages, and limitations provided in Table 1.

[33] introduces a fully distributed P2P control system for Networked Renewable Energy Resources (NRERs), leveraging an MAS framework integrated with the Internet of Things (IoT). The proposed system features a dual-layer architecture: a primary control layer employing droop control for localized power sharing and a secondary control layer utilizing a distributed diffusion algorithm for network-wide customized power sharing. The architecture integrates both local and global communication systems. This approach ensures stable voltage and frequency regulation while promoting efficient distributed energy management. This setup enables real-time distributed control, improving scalability, resilience, and adaptability in microgrids. Despite its scalability and efficiency, the system faces challenges related to communication latency, system complexity, security vulnerabilities, and dependency on stable connectivity. The design also lacks explicit consideration of ER placement or transmission losses between buses, focusing instead on the communication and

control layers. To enhance the system, additional features like adaptive ER placement strategies and optimized transmission loss minimization could be integrated, ensuring a more resilient and cost-effective energy network. Simulation results on a modified IEEE 9-node test feeder validate the approach, demonstrating significant operational improvements with a 52.34% reduction in power losses. These findings highlight the system's potential for managing energy distribution in complex networks, particularly in MSML scenarios. Similarly, a bus-based network is employed in [34]. This paper focuses on active distribution networks (ADNs) as aggregators of Distributed Generation DGs participating in power markets. It proposes a MAS-based coordinated scheduling model to optimize DG generation levels and minimize operating costs by adjusting power purchased from the transmission network (TN). ADN agents interact with Distributed Generation (DG) and Market Operator agents to determine optimal power dispatch while balancing supply, demand, and cost efficiency. The scheduling process involves iterative bid volume adjustments, security assessments, and market clearing based on the Market Clearing Price. Key objectives include minimizing operating costs, optimizing energy routing, and reducing transmission losses. The integration of renewable energy sources and energy storage enhances system performance, while coordinated scheduling ensures stability and economic efficiency. By leveraging decentralized decision-making and multi-energy complementary dispatch, the proposed model improves ADN operations and facilitates a dynamic, market-driven power distribution network. Performance tests on a system with four suppliers, three buyers, and four ADNs demonstrate effective subscriber matching and power scheduling. The study also accounts for power flow, node voltage, and phase angle limits, offering valuable insights into ADN optimization in power networks. [35] addresses the subscriber matching problem by proposing a distributed electricity trading system for P2P electricity sharing among prosumers. The system uses MAS to facilitate agent coalitions for electricity trading and incorporates a blockchain-based mechanism to ensure secure and transparent transactions. Coalition formation allows prosumers to group together and negotiate electricity trading prices and amounts, thus optimizing local energy transactions. A decentralized trading negotiation protocol ensures autonomous price negotiation without a central controller allowing dynamic pricing adjustments for better market responsiveness. The system's objective functions include minimizing trading costs by reducing transaction costs while maintaining economic fairness, enhancing energy utilization efficiency through coalition-based trading, improving scalability and adaptability with a layered architecture that integrates diverse prosumers, and ensuring security and transparency via blockchain-based verification mechanisms. By integrating these components, the proposed trading system enhances energy distribution efficiency, market participation, and resilience in a decentralized electricity trading framework within ADNs. However, it was applied in an ADN without considering all power routing functions, such as transmission paths discovery. The proposed solution could be extended to a power network with multiple ERs to address other power routing functions.

However, [36], [37], [38] introduce a distributed protocol for achieving optimal routing using consensus techniques, with each paper having its own specific targets. Reference [36] introduces a MAS framework to coordinate ERs in a DC microgrid, using a centralized master node to assign producers to consumers. The paper proposes a discrete biased-min consensus (DBMC) algorithm for optimal power trading in DC microgrids, aiming to minimize power loss and alleviate line congestion. In this approach, the optimal power trading problem is formulated as an optimal routing discovery issue, where ERs exchange information and update their state values based on the DBMC algorithm until the system converges to the minimum transmission loss. The objective function focuses on minimizing the power loss during transmission and optimizing the routing of energy. However, this approach raises concerns about security and network complexity. It was verified using a 12-bus DC Multi-ER system and a 201-bus distribution system. In [37], a distributed gossip-based algorithm is introduced for equitable energy resource allocation in microgrids, though it faces challenges such as increased time complexity and communication overhead with larger networks. The algorithm was tested using a network composed of multiple nodes, each representing a microgrid with either surplus or deficient energy. The algorithm regulates total energy transmission over a given period, ensuring that surplus energy from certain grids can be shared with others experiencing shortages. The objective function focuses on optimizing energy transmission schedules based on these forecasts, with the goal of maintaining a balance between supply and demand. Although the current implementation focuses on regulating total energy transmission quantities, it envisions future improvements that could enable detailed real-time power transmission regulation using advanced techniques such as linear regulation, commonly employed in demand response systems. This method is grounded in the theory of cyber-physical integration, where energy and information infrastructure are co-located and controlled through energy routers, facilitating efficient energy-sharing and transmission across the network. [38] presents a blockchain-based transaction consensus strategy for energy trading, addressing the energy subscriber matching problem but excluding ERs. The algorithm uses key parameters such as the Distribution Location Marginal Price and the transmission system's Marginal Price. These prices reflect the clearing value at different locations within the distribution system and are essential in calculating energy costs, congestion charges, and transmission losses. The objective function of the optimal power flow aims to minimize the system's cost while satisfying constraints related to unit outputs and real-time load requirements. The DC approximation method is employed to model the distribution network, incorporating constraints on power flow, voltage angles, and system capacity. The Lagrange multiplier solution is applied to the minimum cost function for the operating unit, and a decentralized trading mechanism is proposed, specifically a P2P trading model that facilitates fair competition and user-centered participation. The algorithm in [38] was verified using a modified IEEE 13 bus test feeder system for distribution network. Each participant functions as a node in a blockchain network, creating a decentralized system for power information exchange. Reference [39] introduces two consensus algorithms within an MA framework. The first algorithm aims to align the incremental cost of each DG with the state of the leader agent. The second algorithm estimates the global power mismatch by modifying a first-order average consensus algorithm with a correction term. This approach focuses on local information exchange between neighboring agents, eliminating the need for extensive communication. To maintain a balance between energy supply and demand, the paper proposes an effective control strategy for the ER. The authors center their attention on power networks consisting of one ER connected to the main grid. However, [40] explores consensus control to enhance the security of energy infrastructures, specifically for recovering networks during link failures. The main objective function involves optimizing the accuracy and security of state estimation while ensuring the robustness of networked coordination in EI. This method enables intelligent agents in a multi-agent system (MAS) to estimate the power grid state based on local measurements and shared information from neighboring agents. To address cyber-attacks and network failures, a consensus-based update strategy ensures continued coordination despite topology variations. The key contributions include a fully distributed state estimation scheme with near-optimal performance, integration of consensus control for security against anomalies, and a recovery mechanism to detect and mitigate misbehaving nodes, ensuring network stability. Finally, [41] utilizes agent-based modeling for energy transmission scheduling, aiming to maximize renewable energy use and reduce peak loads on the primary grid in a single ER network. Collectively, these works demonstrate the potential of MAS frameworks and consensus algorithms for improving energy routing, while also highlighting problems such as network complexity, communication overhead, and scalability challenges.

In contrast to the previously mentioned approaches, [42] introduces a fully distributed power routing protocol inspired by ad hoc computer networks. The proposed system aims to optimize power distribution and ensure reliable operation by utilizing intelligent power routing nodes that operate in a decentralized manner, communicating and collaborating through an ad hoc wireless network. The proposed power routing protocol was verified through a dynamically changing network simulated using Gnucap. The setup initially consists of 5 smart nodes. Despite being published earlier, this paper remains a valuable reference for addressing power routing problems within an MA architecture. Its key advantage is its distributed control mechanism, which relies on node communication, making it well-suited for EI-based networks.

By combining the MA architecture and the RL computation, [43], [44] solve different power routing problems. Reference [43] presents a distributed power routing protocol based on Multi-Agent Reinforcement Learning (MARL) and Q-learning, aiming to find optimal power routes with minimum power losses for a source-load pair while considering maintenance during failures. Unlike traditional methods such as graph traversal or the shortest path algorithm, this approach operates within each ER, utilizing information from neighboring routers. It was validated in a network consisting of 9 ERs. In contrast, [44] tackles energy subscriber matching and transmission scheduling within an interconnected MG system using Multi-Agent Deep Reinforcement Learning (MADRL). This paper presents a decentralized energy management system for an interconnected multi-microgrid (MMG) network, where each microgrid operates autonomously with its controller. The optimization model is formulated as a Markov game and solved using MADRL. The state variables include electricity prices, state of charge of the energy storage system, forecasted thermal and electrical loads, power generation from distributed generation, wind turbines, and photovoltaic systems, as well as node voltage levels. The action space consists of active and reactive power control variables for ESS, DG, PV, and power-to-heat units. The reward function aims to minimize the total operational costs, including electricity purchase costs, fuel and operational costs of DGs, gas consumption costs, and voltage stability penalties. The system is constrained by heat and power limitations, ensuring the stable operation of the MMG network. The proposed energy management strategy optimizes power distribution, enhances economic benefits, and ensures system security while maintaining voltage stability across interconnected microgrids. The proposed protocol was validated in a 16-node multi-MG system. Each MG controller is modeled as an intelligent agent that makes decentralized decisions based on both local and external information. However, while the approach performs well in various scenarios, it does not incorporate ERs for energy flow management, instead utilizing switches.

Using a combination of graph theory and MAS architecture, [45], [46], [47] effectively manage active power flows in power systems. In [46], the problem is formulated as a minimum-cost flow problem, considering both the shortest path and maximum power flow. To solve this problem, the paper utilizes the Scaling Push-Relabel algorithm, implemented within a MA environment. It was verified through a 3-bus test network. In [47], the OPF is treated as a minimum cost flow problem, which is addressed using the successive shortest path algorithm. The agents represent the prosumers in the network. The complexity of the successive shortest path algorithm is specified as $O(N^2 LB)$, where B is an upper limitation on each node's highest supply (demand), N is the number of nodes, and L is the number of links. In [47] a

TABLE 1. Advantages, limitations and applicability of power routing strategies based on MA architecture.

Ref.	Advantages	Key Limitations	Applicability
[33] Multi-Agent P2P Control for NRERs with IoT.	P2P energy Trading, Real-time processing, Local and global optimization, cost and power savings.	Communication latency, High system complexity, Security vulnerabilities in IoT, Dependent on stable connectivity, Simplified assumptions.	Smart grids with diverse RERs, Decentralized power systems, IoT-integrated networks, Future scalable energy systems with Multiple ERs.
[34] ADN Coordination in Power Market.	Minimizes operating costs, considers transmission line power flow, node voltage, and phase angle limits, Uses MAS for coordinated scheduling.	Focused on ADN coordination, Simplified assumptions about power routing functions.	Power systems with ADN, Bi-directional ADN-TN integration for market participation, Future scalable energy systems with Multiple ERs.
[35] Distributed P2P Electricity Trading.	Facilitates secure and transparent trading with blockchain.	Applied only to ADN without fully incorporating power routing functions.	Networks requiring secure and decentralized electricity trade mechanisms. Future scalable energy systems with Multiple ERs.
[36] Distributed Protocol Using Consensus.	Exchanges state information among neighboring ERs until convergence.	Limited to DC microgrids, Assumes ideal communication for consensus achievement.	DC microgrids with multiple ERs. Future scalable energy systems with Multiple ERs.
[37] Distributed averaging iteration for equitable energy allocation.	Low communication requirements for neighboring nodes.	Increased time complexity with larger networks, Limited to microgrid systems.	Decentralized consensus-based resource management. Future scalable energy systems with Multiple ERs.
[38] Blockchain and Consensus for EI.	Secure transactions, MA cooperation and sharing among entities.	Focused solely on subscriber matching.	Secure and transparent trading in MA energy systems, Coordination among energy entities in the EI.
[39] Consensus Algorithms for Energy Balance.	Local information exchange, Effective ER control for energy supply-demand balance.	Focused on single ER connected to the main grid.	Energy networks with single ER.
[40] Consensus Control for EI Security.	Enhances EI security, Distributed recovery strategy for robust EI networks.	Does not address broader energy routing or scheduling.	Cyber-attack recovery in distributed EI, Future scalable energy systems with Multiple ERs.

TABLE 1. *(Continued.)* Advantages, limitations and applicability of power routing strategies based on MA architecture.

[41] Scheduling Strategy for ER.	Maximizes renewable energy utilization, Reduces peak load burden on primary grid.	Focused on single ER systems, Addresses only transmission scheduling.	Networks with single ER, Scheduling for renewable integration and load mitigation.
[42] Fully Distributed Power Routing Protocol.	Fully distributed system, Utilizes intelligent power routing nodes for optimized power distribution.	Limited details on system scalability.	Decentralized power routing in dynamic and distributed networks, Real-time energy distribution in wireless-enabled systems, Future scalable energy systems with Multiple ERs.
[43] MARL for Power Routing and Maintenance.	Handles maintenance phase in case of failures, Relies on local information from neighboring routers for decision-making.	High computational power for large networks. Only addresses the energy efficient path problem.	Energy networks with dynamic routing requirements, Systems needing failure recovery protocols.
[44] MADRL for Energy Management.	Models interconnected MMG systems, Decentralized decision-making.	Focuses on MMG systems.	Interconnected MMG systems for energy and heat management, Future scalable energy systems with Multiple ERs.
[45], [46][47] Graph Theory and MAS Architecture for Power Flow.	Distributed implementation improves scalability in ADNs, Demonstrates the applicability of graph theory in MAS frameworks.	Focuses on OPF, distinct from power routing, Computational complexity increases with larger networks.	Networks needing distributed optimization for power distribution and routing decisions, Future scalable energy systems with multiple ERs.

distributed implementation of the cost-scaling push-relabel algorithm is proposed for effectively managing power flow in ADNs. It was verified through a radial configuration of a 5-bus test network. An agent in papers [45], [46], [48] represents a node (bus) in the network. Reference [47] only mentioned that each bus has a power router. These papers demonstrate how graph theory can be applied in a MAS architecture in power networks formed by multiple ERs.

The reviewed approaches, employing MA architectures, exhibit significant variations in addressing power routing characteristics. TABLE 4 highlights these differences in detail. References [36], [42], and [44] focus on energy-efficient path selection and energy subscriber matching, while [37] and [41] tackle transmission scheduling.

Meanwhile, [35], [38], and [39] address the energy subscriber matching problem, and [34] uniquely addresses both energy subscriber matching and transmission scheduling.

Regarding control architecture, [33], [36], [38], [39], [42], [43], and [44] adopt a decentralized control structure, prioritizing autonomous operation and adaptive behaviors. This distributed decision-making contrasts with the centralized approaches found in other works. [45] employs virtual agents ('as' and 'at') representing source and sink nodes, focusing on centralized aspects in scenarios involving two sources (R1 and R2) and two loads (R3 and R5) (FIGURE 5). Self-stabilizing and self-healing properties are notable in the algorithms presented in [46] and [47], enabling adaptation to transient changes in the network. However, centralized aspects persist in these papers. References [45], [46], and [47] emphasize optimal power flow within the network using MA architecture. These papers have been reviewed to highlight the application of their proposed approaches in an EI-based network to solve the power routing problem

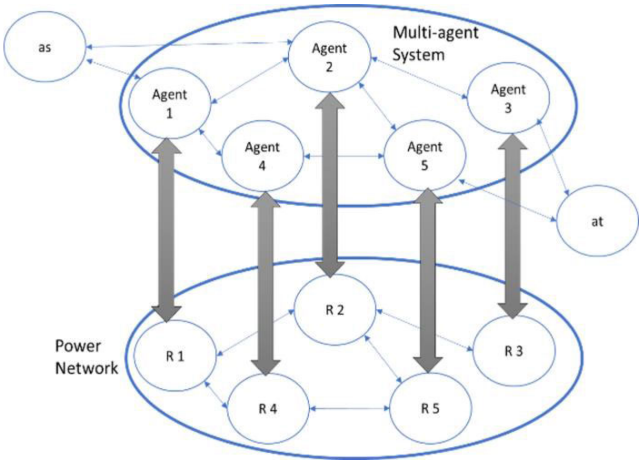

FIGURE 5. Multi agent architecture.

B. ENERGY ROUTING BASED ON AI COMPUTATION

The adoption of models and algorithms rooted in AI has not only become prevalent but also imperative [50], [51], [52]. Recently, AI has played an increasing role in addressing energy management challenges in complex energy systems. This section explains how AI computation is used in power networks and analyzes its contributions to power routing characteristics. Table 2 shows the advantages, limitations, and applicability of each paper, along with the power routing characteristics highlighted in Table 4.

A model-free Deep Reinforcement Learning (DRL) algorithm was implemented in [49] to address the energy management problem by controlling the power output of ERs and DGs within sub-grids. The agent interacts with the EI system as the environment, using system state observations to determine actions based on a learned control policy. This algorithm was validated using a network composed of nine nodes, each representing a sub-grid. Despite its potential, DRL poses challenges, including high computational costs, the need for extensive data for effective learning, and difficulties in acquiring historical data or modeling system dynamics. Additionally, the performance of DRL depends heavily on hyperparameter tuning, requiring significant expertise and experimentation. References [53] and [54] explore advanced control frameworks using deep learning (DL) and neural network (NN)-based reinforcement learning for energy management and routing in power networks. Reference [53] presents a DL-based control framework for wide-area power networks, achieving global optimization through localized information exchange among neighboring ERs. A model-free deep reinforcement learning approach, such as the Actor-Critic algorithm, is employed to achieve real-time adaptive energy routing. Convolutional Neural Networks (CNNs) are used for demand forecasting, while graph-based algorithms determine the most efficient power transmission paths. This integrated approach ensures efficient energy management, enhances network resilience, and enables optimal power routing in a dynamic and decentralized EI environment. However, challenges include the need for substantial training data, high computational complexity, and limited scalability, which may hinder real-time applicability in dynamic conditions. Reference [54] uses an artificial neural network-based reinforcement learning method for optimal energy routing, incorporating a Q-learning algorithm to dynamically adjust routes based on renewable energy fluctuations and demand. The objective functions aim to minimize operating cost, defined as a combination of gas boiler and combined heat and power costs, as well as renewable energy system costs. Additionally, power loss minimization is formulated based on transmission losses in network connections, while environmental cost minimization accounts for emissions generated from fossil fuel-based power sources. The optimization strategy leverages RL to adaptively manage the energy routing process, ensuring high efficiency and cost-effectiveness in energy transmission. This approach was verified through a network formed by 7 ERs. While effective, the approach relies heavily on high-quality training data, and the authors did not detail the training process of the multi-layer NN used to approximate Q values. Furthermore, generalization to scenarios outside the training domain and hyperparameter tuning for optimal performance remain significant challenges.

C. ENERGY ROUTING BASED ON METAHEURISTIC APPROACH

Metaheuristics provide powerful optimization tools for power routing protocols, enabling efficient routing path selection, load balancing, and resource allocation, leading to a more resilient, reliable, and efficient energy distribution network. Table 3 shows the advantages, limitations, and applicability of each approach, along with the power routing characteristics highlighted in Table 4.

The Firefly Algorithm (FA) was utilized in [55] and [56] to tackle the subscriber matching problem, inspired by the

TABLE 2. Advantages, limitations and applicability of power routing strategies based on AI.

Ref.	Advantages	Limitations	Applicability
[49]	Effective control of power output for ERs and DGs within sub-grids, Suitable for dynamic networks.	Computationally expensive, requires large amounts of data, and hyperparameter tuning.	Suitable for small to medium-sized systems, Real-time energy management tasks.
[53]	Achieves global optimization by exchanging local information, Reduces the need for extensive communication between ERs.	Require large amounts of data, has Computational complexity, Real-time applicability may be constrained in dynamic network.	Suitable for real-time control in small-scale or stable environments but may struggle in highly dynamic, large-scale systems.
[54]	Dynamic adjustment to energy paths.	Dependent on the training data. Generalization is not addressed. Hyperparameter tuning.	Less effective in large-scale system where data scarcity and adaptability are critical.

social behavior of fireflies. While [55] focuses on solving the SM problem based on Euclidean distance and energy price, it overlooks the impact of ER, link impedance, and voltage drops, which can increase losses in real SGs. The objective is to match consumers with the best producers in a way that maximizes overall satisfaction while minimizing energy costs, power losses, and transmission distances. The algorithm operates in three phases: initialization, fitness calculation, and energy quantity update. During the initialization phase, parameters like energy quantities, pricing, and positions are set up. The fitness of each firefly is evaluated based on an objective function that considers energy demand, supply, power loss, and price. Finally, the energy quantities of both consumers and producers are updated according to the energy available and needed, ensuring that each consumer's demand is met at minimal cost and with minimal loss. This method provides an efficient, decentralized solution for energy routing in complex energy networks, enhancing energy distribution while minimizing operational costs and inefficiencies. The algorithm was verified using an EI network with 17 nodes represented as a graph, where each node represents an ER, a producer, or a consumer. Reference [56] advances by addressing energy-efficient paths in addition to subscriber matching. The algorithm was verified through a network comprising 11 nodes, including 7 producers and 4 consumers. However, both approaches would benefit from incorporating more comprehensive loss models, dynamic data, and improved scalability to handle larger grids and diverse operational challenges. Future work could explore hybrid methods combining FA with techniques accounting for power flow dynamics, congestion management, and real-time decision-making.

The Genetic Algorithm (GA) was applied in papers [57], [58], [59]. In [57], the authors solve the energy subscriber matching problem using GA and determine the EEP using a Path Generator algorithm. The main objective is determining the most efficient way to allocate energy from producers to consumers while minimizing power loss and costs. In [57], solutions are represented as chromosomes, with each chromosome linking producers or groups of producers to a consumer. The fitness of each solution is evaluated by calculating power loss along the paths from producers to consumers. The goal is to find the set of producers and paths that minimize total power loss and cost, ensuring an efficient and reliable energy distribution system. This approach was verified through a network comprising 17 nodes, each representing an ER. However, the GA is used in [58] to solve the energy efficient path selection problem. The GA models solutions as chromosomes and uses crossover and mutation to find energy transmission routes with minimal power loss. A 7-node network graph and a 17-node network graph were used to verify the proposed algorithm. They were generated using Python, with each node representing an ER. It effectively reduces losses, especially over long paths, and outperforms Ant Colony Optimization (ACO) with a 7.75% efficiency improvement. GA's adaptability to complex network dynamics and large solution spaces makes it suitable for various network configurations. In [59], GA was combined with a graph traversal algorithm to identify path sets from source to load, considering power constraints. This work stands out as the first to consider both objectives simultaneously, contrasting with previous strategies that primarily focused on minimizing power losses. The improved unified third version of the nondominated sorting genetic algorithm U-NSGA-III was employed for Pareto optimization, weighing carbon emissions and power losses to select the best solution. Parent-Centric Crossover (PCX) was introduced, leveraging multiple parents for better exploration and avoiding suboptimal results. The proposed approach is a hybrid method, combining the efficiency of DFS and U-NSGA-III, allowing for a larger search space and shorter search times compared to existing multi-objective optimization algorithms. An 11-node network graph was used to verify the proposed algorithm. While [57] focuses on matching energy producers with consumers, [58] extends this to efficient path selection. Reference [59] further enhances the methodology by integrating multi-objective optimization and addressing limitations in traditional genetic operations. However, all methods share common limitations in scalability, centralized control requirements, and the need for dynamic adaptability to handle real-world challenges such as failures, congestion, and demand-side participation. Future improvements could integrate distributed implementation and robust control mechanisms to address these gaps.

ACO has been applied to energy routing problems in SGs in different contexts. In [60], the ACO-based protocol addresses energy demand and supply matching while determining optimal energy paths between consumers and producers. It focuses on two critical routing challenges: subscriber matching and efficient path selection. Building upon this, [61] extends the methodology to include subscriber matching, efficient routing, and transmission scheduling. The protocol in [61] optimizes energy paths to minimize congestion and losses, achieving the most efficient routing configuration. The time complexity of the ACO algorithm, as derived in [61], is expressed as O (n x (n-1) x m x maxIT/2). 'n' represents the number of ER, 'm' represents the number of ants, and 'maxIT' denotes the maximum number of iterations. A 17-node network graph was used to validate the proposed algorithm. Each ER linked to a consumer implements an IACO-based energy routing algorithm to identify the most energy-efficient path between producer-consumer pairs. However, the algorithm's high computational demands and extended time requirements pose challenges for real-time applications, particularly in large-scale networks. Scalability problems arise as network size increases, often leading to suboptimal routing outcomes. Another limitation of ACO lies in its reliance on predefined pheromone trails and heuristics, which restrict adaptability to dynamic changes in smart grid environments. Additionally, the algorithm's performance is heavily influenced by parameter tuning, including pheromone evaporation rates and the balance between exploration and exploitation.

Identifying optimal parameter settings often demands extensive experimentation. Despite these challenges, ACO demonstrates significant potential in energy routing optimization, particularly for medium-sized and relatively stable smart grids. Its ability to optimize multiple routing objectives makes it an effective solution for such networks. To address limitations in scalability, adaptability, and computational demands, future work may explore hybrid approaches or enhanced ACO versions tailored for dynamic and large-scale smart grid applications.

Inspired by the foraging behavior of bees, the Bee Colony Optimization (BCO) is employed in [62] and [63], with distinct implementations and functions. In [62], the BCO algorithm determines the optimal producer-consumer matching based on energy demand and routes energy through the most efficient path, considering transmission cost and delay. This process is essential for identifying the most energy-efficient path, considering both the transmission loss and the available energy resources at each node. The optimization goal is to minimize energy loss and path length while ensuring the demand is met efficiently. This algorithm has not been verified or implemented in a network. In [63], the focus shifts to finding a path with minimal congestion and losses while selecting the optimal energy producers to meet consumer requests within power and time constraints. This algorithm was verified using a network formed by ERs, where the IEEE-30 Bus electric network, and a 9-bus network were modified by replacing each bus with an ER. The BCO-based energy routing protocol enables autonomous and self-organized behavior, allowing agents to make efficient decisions and explore multiple path options for energy routing.

The Discrete-Artificial Bee Colony algorithm (D-ABC), introduced in [64], extends the ABC algorithm for energy-efficient pathfinding in capacity-constrained EI environments. D-ABC employs crossover and mutation during the employed and onlooker bee phases, improving convergence and reducing suboptimal solutions by diversifying strategies. However, these algorithms face limitations such as high computational demands, sensitivity to parameter tuning, and memory-intensive operations in large networks. BCO and D-ABC provide robust energy routing solutions in SG environments, leveraging bio-inspired heuristics to address complex challenges. Their scalability and applicability in large, dynamic networks could be enhanced by integrating adaptive techniques and leveraging computational advances.

The Particle Swarm Optimization (PSO) algorithm has been applied in [61] and [65] to address energy routing challenges in SGs. In [61], PSO is used to select a group of producers and determine the optimal energy allocation to meet consumer demand, focusing on the energy subscriber matching problem. In [65], PSO is employed within a multi-objective optimization framework to balance energy supply and demand by optimizing the energy path between producers and consumers. The protocol involves nodes sending energy request messages and receiving link-state information, with PSO optimizing path selection based on metrics like transmission latency, hop count, distance, and cost. Fitness values are calculated considering the relative importance of these metrics. The algorithm in [65] was verified using a 10-nodes energy network. Due to its rapid convergence and high accuracy, PSO, one of the most widely used intelligent optimization methods, is chosen to solve the virtual energy routing problem to reduce power loss and improve energy efficiency in the Energy Internet. However, the classical PSO algorithm is not suitable for the discontinuous routing problem. Therefore, its discrete form is used in [67], and it was verified through a network formed by 30 buses, transformed into a network with 7 ERs. PSO provides a versatile tool for energy routing with a robust optimization framework. However, challenges such as premature convergence and dynamic network handling need to be addressed. Future improvements could include hybrid methods and dynamic adjustments to enhance its efficiency and scalability in real-world applications.

The Simulated Annealing (SA) algorithm is applied in the power routing protocol proposed in [66] to optimize path selection and scheduling in energy routing. It begins by generating an initial solution using a backtracking method to identify a random path between the source and destination. The energy function evaluates power losses during transmission and conversion, aiming to minimize these losses. Additionally, the protocol addresses congestion caused by intersecting paths at power lines, which can lead to significant losses. This protocol was verified through two networks:

a 7-node energy network and a 17-node network, where each node represents an ER. While the SA-based protocol effectively minimizes power losses and manages congestion, its high computational demands and sensitivity to parameter tuning highlight the need for hybrid methods and dynamic adaptations for large-scale, real-time applications.

Metaheuristic optimization methods are frequently employed in power routing protocols due to their ability to solve complex optimization problems. However, they share common drawbacks, including significant computational complexity when applied to complex networks. Additionally, their performance relies heavily on parameter tuning, such as population size, iteration limits, and mutation rates, which can hinder convergence and lead to suboptimal results if not properly optimized. Referring to Section III, energy routing schemes can be categorized based on their architecture. Centralized approaches, as presented in [58], [59], [61], [63], and [67], rely on a single control node, which simplifies decision-making but introduces challenges related to scalability, single points of failure, and network overhead. Conversely, decentralized methods, as implemented in [55], [56], [57], [62], and [68], distribute decision-making across nodes, enhancing adaptability to dynamic changes and reducing reliance on a central node. However, decentralized approaches often increase communication overhead, as seen in [55], where every node maintains information about all others. Semi-centralized protocols, such as [60], strike a balance but still raise concerns about security, privacy, and the overhead introduced by the central coordinator. Several papers, including, including [63], [64], [66], [67], address congestion management by incorporating power capacity constraints on links and ERs and utilizing multi-packet transmission techniques. In [66], congestion arising from intersecting paths is mitigated through strategies like First in First Out, shortest job first, and Round Robin scheduling. Reference [63] emphasizes the selection of non-congested paths and the transmission of energy in packets to reduce delays and improve link and ER utilization. The simulation results in [64] demonstrate that the D-ABC algorithm outperforms other approaches like ACO [61] and Greedy search [27] in finding congestion-free paths, particularly in large networks. Despite these advancements, some papers in this section do not address congestion management strategies. Specifically, [61] is criticized for disregarding edges and nodes incapable of transmitting power, resulting in a subgraph.

The real-world applicability of metaheuristic-based protocols necessitates addressing diverse scenarios. References [58] and [59] validate their approaches under the MSML scenario, whereas [55], [57], [61], and [66] focus on SSSL and MSSL scenarios. However, the absence of MSML considerations in these works underscores their limitations in handling more complex scenarios. Protocols [62], [64], [65], and [67] restrict their scope to SSSL, overlooking key aspects such as link failures, multiple energy requests, and dynamic changes. For example, [64] fails to address security concerns and system adaptability, while [65] and [67] lack clarity on managing such challenges. The centralized approach in [61] outperforms graph traversal methods but shows limited flexibility for dynamic changes. The decentralized approach in [66] demonstrates effective resource allocation, reduced power loss, and congestion mitigation in MSSL and SSSL scenarios, indicating strong performance. Similarly, MSML-focused protocols in [58], [59], and [63] achieve optimal solutions by balancing power loss, transmission time, and congestion management. In contrast, [60] does not address critical problems like link failures and congestion, limiting its practicality in varied environments. Metaheuristic-based protocols, such as D-ABC [64] and BCO [62], offer innovative solutions for optimizing power distribution in smart grids. However, they face challenges related to computational complexity, parameter sensitivity, and limited scenario coverage. Future research should focus on integrating adaptive techniques, hybrid metaheuristic methods, distributed control architectures, and dynamic routing strategies to enhance scalability, robustness, and real-world applicability.

V. DISCUSSION AND FUTURE DIRECTIONS

Table 4 presents a comparative analysis of various power routing protocols, categorized based on key characteristics. A detailed evaluation of power routing protocols based on MA architecture, AI computing, and metaheuristic optimization reveals that while significant progress has been made in addressing individual challenges, no single protocol comprehensively tackles all aspects. Existing studies often focus on limited combinations of energy routing functions. Subscriber matching appears in multiple protocols, underscoring its role in aligning energy supply and demand for efficient routing. Similarly, the presence of Energy Efficient Path features highlights their importance in minimizing losses and optimizing power flow. Transmission scheduling is included in a few protocols, ensuring that energy is routed at optimal times to prevent overloads and maintain system stability.

Table 4 further classifies protocols based on their architectural approach—centralized, decentralized, or semi-centralized. Centralized algorithms demonstrate strong optimization capabilities for minimizing power losses but rely heavily on complete network information, limiting their scalability in decentralized and dynamic environments. Additionally, such approaches introduce increased infrastructure complexity, security vulnerabilities, and computational overhead. Semi-decentralized protocols attempt to mitigate these issues by balancing computational demands while still relying on network data. This dependency imposes scalability constraints. In contrast, fully distributed algorithms leverage local information from neighboring nodes, making them more adaptable to real-time topology changes, congestion management, and efficient energy routing in decentralized networks.

Failure management [37], [40], [42], [43] and congestion control [38], [43], [63], [64], [65], [66], [67] play a vital role in maintaining network stability in dynamic

TABLE 3. Advantages, Limitations and applicability of power routing strategies based on metaheuristics optimization.

Ref.	Advantages	Limitations	Applicability
[55]	Optimizes the selection of suitable producers in SGs.	Assumes that the minimum Euclidean distance always leads to minimum losses.	Suitable for identifying producers in simpler, idealized SG scenarios.
[56]	Addresses energy-efficient path selection and energy subscriber matching problem.	Relies on simplified models.	Needs improvement for handling real-world grid complexities. Requires further enhancements to scale to larger grids and more diverse scenarios.
[57]	Solves the energy subscriber matching problem, evaluating fitness based on total power losses.	Centralized implementation, Requires complete network information and does not address failures, congestion, or dynamic challenges in real networks.	Effective for matching producers with consumers in controlled scenarios. Lacks scalability for real-world, large-scale systems.
[58]	Optimizes energy path selection, reducing power losses, especially over long transmission paths. Highly adaptable to complex networks.	Centralized implementation, Complete network information. Does not address energy subscriber matching or scheduling. Limited capacity to manage failures and congestion.	Suitable for efficient energy transmission path selection in structured networks. Needs distributed solutions to scale effectively.
[59]	Integrates multi-objective optimization. Considers carbon emissions and power losses as decision variables. Introduces better exploration variables, avoiding suboptimal solutions.	Centralized control. Requires significant computational resources. Needs greater adaptability for dynamic, real-world challenges	Applicable for multi-objective optimization in energy routing scenarios. Useful for balancing environmental and operational factors in energy systems.
[61]	Efficient for medium-sized grids; enables optimization of multiple energy routing aspects.	Scalability problem, adaptability. Computational and parameter tuning demands.	Suited for grids with moderate size and stability. Hybrid approaches may be applied to larger, more dynamic grids.
[62] [63]	Enables autonomous and self-organized decision-making. Facilitates multiple path exploration for efficient routing. Adapts dynamically to changes in grid topology.	Computational complexity increases with larger and more complex network topologies. Sensitive to parameter tuning based on network size. Relatively high transmission cost and delay if improperly configured.	Optimal producer-consumer matching based on energy demand [62]. Routing with minimal congestion and losses while meeting time and power constraints ([63]). Applicable in dynamic smart grid environments with moderate node counts.
[64]	Enhances exploration through common node crossover and mutation. Improves solution convergence in local searches.	Parameter tuning is time-consuming. Memory-intensive due to storing the entire population. Scalability challenges in large networks.	Energy-efficient path selection in capacity-constrained EI environments. Effective for optimizing energy routing in small networks.
[65]	Achieves a balance between energy supply and demand through multi-objective optimization. Incorporates multiple metrics for robust decision-making. Supports decentralized operation, enhancing scalability and adaptability in dynamic smart grid environments.	Susceptible to premature convergence, limiting the exploration of global optima. High computational complexity due to multi-metric evaluations.	Suitable for decentralized energy management with multiple producers and consumers in dynamic networks. Ideal for real-world applications where decentralized control and multi-objective optimization are prioritized.
[66]	Effectively minimizes power losses during transmission and conversion. Robust in managing congestion in energy networks. Provides a strong framework for static routing challenges.	High computational demands. Sensitive to parameter tuning. May struggle with dynamic network conditions or real-time applications.	Suitable for static energy routing problems where paths and conditions are predictable. Potential for use in large-scale applications with hybrid or dynamic adaptations.

networks. Protocols incorporating these mechanisms help mitigate disruptions caused by ER failures or congestion, ensuring continuous and reliable power transmission. Many protocols require knowledge of the entire network to function effectively. While this improves decision-making accuracy, it also increases communication overhead, particularly in large-scale networks.

Real-world energy networks require power routing protocols that can dynamically adapt to diverse operational conditions, including MSML, SSML, MSSL, and SSSL. However, as Table 4 shows, current research has yet to develop a comprehensive solution that addresses all these scenarios simultaneously.

Despite these advancements, many existing protocols still face significant gaps, particularly in congestion management, real-time network adaptation, and cybersecurity. These aspects remain underexplored, especially in decentralized, dynamic and large networks, highlighting the need for more comprehensive solutions.

Handling network failures in decentralized energy systems remains a critical challenge. A viable solution is the use of multiple ERs to enhance fault tolerance and ensure resilient energy routing. These routers can dynamically redirect energy flow through alternative paths when failures occur, minimizing disruptions and maintaining stable power distribution. Another challenge lies in addressing the unpredictability of demand and supply, especially with the increasing integration of renewable energy sources. Current algorithms often struggle to handle such variability, as they typically rely on more stable, predictable conditions for optimal path planning. Future energy routing protocols will need to incorporate real-time data and predictive models, using advanced AI and machine learning techniques, to better adapt to these dynamic conditions. A more dynamic, adaptive approach is necessary, one that can continuously update its knowledge base and optimize routing decisions. Many power routing algorithms struggle with inefficiency in dynamic and large systems. To address these challenges, distributed optimization can replace traditional centralized approaches, using MAS to balance computation across multiple nodes while ensuring fast decision-making.

In the context of congestion management within energy routing protocols, several strategies have been proposed, yet there remain significant gaps that need to be addressed for more efficient and scalable solutions. Existing approaches often focus on power constraints, such as limiting the maximum capacity of ERs and network links. While this method can provide basic congestion alleviation, it does not fully account for dynamic fluctuations in energy demand and supply, especially in decentralized networks where these variables can change rapidly. Some studies have also introduced the concept of dividing the energy flow into multiple ''power packets'' to reduce congestion, but this strategy can be inefficient when dealing with highly variable network conditions. To address these gaps, future research should consider integrating more adaptive mechanisms, such as real-time monitoring and dynamic allocation of network resources, allowing for flexible routing decisions that respond to fluctuating energy demands. Furthermore, the implementation of MAS could improve congestion management by enabling decentralized decision-making, where individual agents can autonomously adjust their routing decisions based on local network conditions. These approaches can offer a more robust and adaptive response to congestion in dynamic energy systems, ensuring better utilization of network resources and enhanced system performance.

As mentioned earlier, cybersecurity challenges are still not well explored in the domain of energy routing protocols. Decentralized energy systems are increasingly vulnerable to cyber-attacks that could manipulate routing decisions, leading to suboptimal paths, overloads, or system failures. As routing relies on real-time data and predictive models, ensuring data integrity is crucial. Cyber-attacks could disrupt path selection, causing energy wastage, congestion, or imbalances. Future improvements in securing energy routing protocols could leverage advanced cybersecurity techniques such as secure multi-party computation (SMPC) and blockchain. SMPC ensures data privacy and prevents manipulation, while blockchain provides a transparent, immutable ledger to secure energy trading and routing decisions. However, integrating these solutions requires further research to address practical implementation challenges and computational overhead, which could impact real-time decision-making in large-scale networks.

Implementing power routing algorithms in real-world systems presents several practical challenges beyond theoretical modeling. One major issue is computational overhead, as many metaheuristic and AI-driven algorithms require significant processing power, making real-time decision-making difficult. High-dimensional search spaces and complex optimization objectives increase execution time, especially in large-scale networks. Hardware limitations further constrain implementation, as embedded systems and IoT devices used in smart grids often have limited processing capacity, memory, and energy resources. The integration of parallel computing and edge computing can help alleviate these constraints but requires additional infrastructure investments. Moreover, real-world network dynamics, such as fluctuating demand, unpredictable failures, and communication delays, create challenges that theoretical models often oversimplify.

To summarize this discussion, a comparative table (Table 5) is provided, offering a comparative analysis of different energy routing protocols, highlighting their strengths, weaknesses, and ideal applications in the context of decentralized energy systems. Metaheuristic optimization techniques excel at finding optimal paths and reducing energy losses, making them suitable for relatively stable network environments. However, their application is often challenged by high computational demands and sensitivity to parameter tuning, which can affect real-time decision-making in energy networks. To enhance their efficiency, adaptive parameter tuning techniques, such as reinforcement learning-based adjustments, can be integrated to optimize performance dynamically. Additionally, hybrid approaches combining metaheuristics with machine learning can improve convergence speed and solution accuracy while reducing computational costs. Parallel processing on GPUs and distributed computing frameworks can further accelerate computations, making metaheuristic-based power routing more scalable. AI computing techniques offer adaptability and real-time decision-making capabilities. These approaches are well-suited for dynamic, evolving networks and can autonomously predict and adjust to network conditions. However, their high computational cost and need for large training datasets are notable limitations. Graph Neural Networks and network flow optimization techniques can be used to enhance scalability by efficiently modeling energy transmission paths. MA architectures stand out for their decentralized nature, making them ideal for distributed energy networks. These protocols offer high scalability and flexibility, enabling them to handle dynamic topologies and congestion man-

TABLE 4. Power routing protocols characteristics: MA architecture, Metaheuristic optimization, and AI computation-based methods.

Ref.	SM	EP	TS	Sec	PC	Scenarios	F	CM	Cen	Dec	Semi-Cen	NI
[33]						MSML				✓		
[34]	✓		✓		✓	MSML				✓		
[35]	✓			✓		MSML				✓		
[36]	✓	✓			✓	SSSL				✓		
[37]			✓			SSSL	✓			✓		
[38]	✓			✓		MSML		✓		✓		
[39]	✓									✓		
[40]				✓			✓			✓		
[41]			✓			SSSL, MSSL			✓			
[42]	✓	✓				SSSL	✓			✓		
[43]		✓			✓	SSSL	✓	✓		✓		
[44]	✓	✓			✓	MSML				✓		
[45][46][47]		✓			✓	SSSL				✓		
[48]	✓	✓				SSSL			✓			
[49]	✓	✓			✓	SSSL			✓			✓
[53]		✓				SSSL				✓		✓
[54]		✓			✓	SSSL			✓			✓
[55]	✓					SSSL MSSL				✓		✓
[56][57]	✓	✓				SSSL MSSL			✓			✓
[58]		✓			✓	MSML, SSSL SSML, MSSL			✓			✓
[59]	✓	✓			✓	MSML SSSL SSML MSSL			✓			✓
[60]	✓	✓			✓	MSML					✓	
[61]	✓	✓			✓	SSSL, MSSL MSSL			✓			
[62]		✓			✓	SSSL				✓		
[63]	✓	✓			✓	MSML SSSL SSML, MSSL		✓	✓			
[64]		✓			✓	SSSL		✓	✓			
[65]	✓	✓				SSSL			✓			
[66]		✓	✓			SSSL MSSL		✓	✓			✓
[67]		✓			✓	SSSL		✓	✓			✓

SM: Subscriber Matching, EP: Energy Efficient Path, TS: Transmission Scheduling, Sec: Security, PC: Power Constraints, F: Failure, CM: Congestion Management, Cen: Centralized, Dec: Decentralized, Semi-Cen: Semi-Centralized, NI: Network Information.

TABLE 5. Strengths, weaknesses and ideal applications of different approaches.

Approaches	Strengths	Weaknesses	Ideal Applications
Meta-heuristic Optimization	Well-suited for optimal pathfinding and minimizing energy losses. Effective in stable environments.	Requires high computational power required. Limited flexibility in dynamic, real-time scenarios. Scalability issues in large networks.	Stable networks.
AI Computing	Enhances real-time decision-making. Enables Autonomous adaptation to changing network conditions. Improves scalability and fault tolerance.	High computational costs. Reuires large datasets for training.	Real-time network adaptation. Predictive maintenance and fault management.
MA Architecture	Enables decentralized decision-making, reducing reliance on central systems. Highly scalability and flexibility. Well-suited for congestion management and dynamic topologies.	Coordination among agents can become complex in large networks. Possible delays in decision-making under network stress.	Decentralized energy networks. Congestion management, dynamic energy routing.

agement effectively. However, coordination among agents in large-scale networks can become challenging.

Therefore, future protocols should integrate metaheuristics, AI, and MA architectures to address the challenges while also ensuring scalability, adaptability, and security for real-world applications. Therefore, hybridizing metaheuristic optimization techniques with AI methods, such as Reinforcement Learning, can enable real-time adaptation to dynamic network conditions, reducing reliance on large-scale computations. Additionally, the use of edge computing and data-efficient AI algorithms can alleviate the high computational demands of AI techniques. In MA architectures, implementing agent clustering and decentralized coordination can address scalability issues, while autonomous decision-making through reinforcement learning can enhance agent autonomy.

However, there are some challenges that can arise when using hybrid methods. The integration of AI and ML into energy routing protocols faces key challenges, including data scarcity and the need for specialized AI models. Data scarcity limits AI training in dynamic energy systems, requiring data-efficient methods like reinforcement learning and few-shot learning. High computational demands of AI models hinder real-time decision-making, which can be mitigated through edge computing and distributed AI. Future developments should focus on transfer learning, federated learning, and optimized AI architectures to improve scalability, adaptability, and real-time responsiveness, ensuring resilient and sustainable energy networks.

The integration of these approaches presents a promising avenue for future research. Hybrid energy routing protocols combining the strengths of metaheuristics, AI, and MA systems could address the complexities of dynamic, decentralized energy systems. Future work should focus on effectively integrating these methods to improve scalability, adaptability, and the security of energy routing. AI-based models could predict energy demand and supply fluctuations, enabling real-time optimization of energy flow. Multi-agent frameworks could decentralize decision-making, enhancing system robustness and reducing vulnerabilities to failures. Additionally, incorporating blockchain or other security measures should be considered to protect against cyber-attacks and ensure the confidentiality and integrity of routing decisions.

In conclusion, the integration of AI, metaheuristics, and MA systems offers a promising path forward for building more resilient and efficient energy routing protocols, with the goal of creating sustainable and decentralized energy networks capable of supporting the transition to renewable energy.

VI. CONCLUSION

This paper provides a significant contribution to the research field, particularly in shaping the future of energy routing within the context of EI. It reviews and highlights power routing protocols, emphasizing the advantages of incorporating Metaheuristic optimization and AI computation into MA architecture. Metaheuristics optimization effectively enhances energy route selection. AI computation plays a crucial role in enhancing the intelligence and adaptability of agents. By integrating them into MA architecture, agents can make informed decisions, optimize energy utilization, manage network congestion, adapt to dynamic conditions, and enhance overall system efficiency and reliability. This combination leverages the strengths of metaheuristics for optimization and AI for intelligent decision-making within a collaborative MA environment.

Future research will explore other promising approaches such as graph theory [30], [69] and game theory [70], [71], expanding the research scope in this domain. Additionally, future efforts will focus on developing a novel energy routing architecture that integrates DC distribution networks with ERs capable of covering all critical energy routing functions, including real-time power flow control, fault tolerance, and congestion management. This new ER design will be simulated and tested in various decentralized network scenarios to evaluate its scalability and efficiency. Additionally, hybrid methodologies that combine AI, MAS, and metaheuristics will be explored to enhance real-time decision-making and network adaptability. Advanced AI techniques such as deep reinforcement learning, federated learning, and transfer learning will be investigated to improve routing intelligence while reducing computational complexity. Another crucial direction for future studies is the implementation of blockchain-based security mechanisms to enhance resilience and support decentralized energy routing protocols. These security frameworks will ensure data integrity, prevent cyber-attacks, and maintain stable energy transactions across distributed networks. Additionally, real-world implementation and large-scale simulations using edge computing and cloud-based frameworks will be pursued to evaluate the feasibility of proposed methodologies in practical energy systems.

By integrating these advanced approaches, future energy routing protocols can achieve greater efficiency, adaptability, and robustness, paving the way for more intelligent, decentralized, and resilient energy networks capable of supporting the transition to renewable energy.

One notable aspect highlighted in this review is the potential of distributed protocols to address power routing challenges, especially in large networks. This perspective indicates a promising future for distributed protocols in tackling the complexities of energy routing and optimizing network performance.

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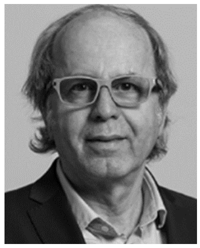
AMANI FAWAZ (Graduate Student Member, IEEE) received the Diploma of Electrical Engineering degree from the École supérieure d'ingénieurs de Beyrouth (ESIB), Saint Joseph University of Beirut (USJ), Lebanon, in 2019. She is currently pursuing the Ph.D. degree in electrical and energy engineering with USJ, specializing in power routing protocols for decentralized energy networks. Her research interests include the energy internet, smart grids, renewable energy integration, and the application of machine learning and metaheuristics in energy routing problem. She has contributed to several peer-reviewed publications and has received support from organizations, such as the Agence Universitaire de la Francophonie and the Conseil National de la Recherche Scientifique-Liban.

IMAD MOUGHARBEL (Member, IEEE) received the Diploma of Electrical Engineering degree from the École Centrale de Lyon, France, in 1977, and the Ph.D. degree in engineering and power electronics from the Université d'Aix-Marseille, in 1980. In 1982, he joined the Department of Electrical Engineering, Lebanese University, Beirut. Since 1990, he has been collaborating with multiple research labs and universities in Lebanon, France, and Canada. After retiring from Lebanese University, he collaborates with professors at the Electrical Department, École de Technologie Supérieure, Montreal, Canada, as a Research Associate, a Visiting Professor, and a Senior Lecturer, in 2017. He has published papers in international peer review scientific journals and conferences, in power electronics, renewable energy, numeric control, wireless sensor networks, and smart grids.



KAMAL AL-HADDAD (Life Fellow, IEEE) received the B.Sc.A. and M.Sc.A. degrees in electrical engineering from the University of Québec à Trois-Rivières, Trois-Rivières, QC, Canada, in 1982 and 1984, respectively, and the Ph.D. degree in electrical engineering from the Institut National Polytechnique, Toulouse, France, in 1988. Since June 1990, he has been a Professor with the Electrical Engineering Department, École de Technologie Supérieure, Montreal, QC, Canada, where he has been the holder of the Canada Research Chair of the Electric Energy Conversion and Power Electronics, since 2002. He is currently a Consultant and has established very solid link with many Canadian industries. He is a Fellow Member of Canadian Academy of Engineering. He was the IEEE IES President 2016–2017, an Associate Editor of IEEE Transactions on Industrial Informatics, the IES Distinguished Lecturer, and a recipient of the Dr.-Ing. Eugene Mittelmann Achievement Award.

HADI Y. KANAAN (Senior Member, IEEE) received the Diploma degree in electromechanical engineering from Saint Joseph University of Beirut (USJ), in 1991, the Ph.D. degree in electrical engineering from the École de Technologie Supérieure (ETS), Montreal, Canada, in 2002, and the Habilitation à Diriger des Recherches (HDR) degree from the Université de Cergy-Pontoise, Paris, France, in 2009. He is also an Associate Professor with ETS, Canada, since 2021. He is currently a Full-Professor and the Director of the Doctoral School of Sciences, Engineering and Technology, USJ. He has co-authored one book, two book chapters, one patent, and more than 280 technical papers published in international journals and conferences. His research interests include modeling and control of switch-mode converters, modern rectifiers, power factor correction, active power filters, and grid-connectivity of renewable energy systems.