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A Systematic Review of Isolated Water and Energy Microgrids: Infrastructure, Optimization of Management Strategies, and Future Trends

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Abstract: Isolated water and energy microgrids (IWEMGs) serve as vital solutions for enhancing the well-being of remote and rural communities, particularly in areas where water and energy resources are scarce. This has spurred research into the interdependence between the water and energy sectors (water–energy nexus), a field that has grown in response to technological advancements. Through a systematic optimization framework, this review critically evaluates the integration of various technologies within IWEMGs, encompassing infrastructure, management, and strategic planning, while considering economic and social impacts. IWEMGs incorporate diverse technologies for the infrastructure, management, and strategic planning of water and energy resources, integrating economic and social considerations to inform decisions that affect both immediate and long-term sustainability and reliability. This article presents an exhaustive review of the literature on IWEMG management, employing an approach that synthesizes existing studies to enhance the understanding of strategic IWEMG management and planning. It introduces a structured taxonomy for organizing research trends and tackling unresolved challenges within the field. Notably, the review identifies critical gaps, such as the lack of comprehensive data on water demand in isolated locations, and underscores the emerging role of game theory and machine learning in enriching IWEMG management frameworks. Ultimately, this review outlines essential indicators for forthcoming research, focusing on the optimization, management, and strategic planning of IWEMG resources and infrastructure, thereby setting a direction for future technological and methodological advancements in the field.

Keywords: water–energy microgrid; optimization; water–energy nexus; planning; management

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1. Introduction

Sustainable development of rural and remote communities is crucial. Isolated water and energy microgrids (IWEMGs) are fundamental solutions to address the challenges in providing these services, promoting sustainable development in these communities. The coordinated interaction between these two domains can ensure the water and energy security necessary for the progress and well-being of marginalized areas, further fostering overall sustainability [1]. United Nations' studies reveal that the potable water supply has become a significant issue due to its limited availability and exponentially increasing demand [2]. Consequently, global water distribution systems are compelled to explore alternative sources such as seawater, groundwater, and precipitation. In efforts to replace diminishing potable water sources, entities often resort to energy-intensive processes like desalination or groundwater pumping [3,4]. As a result, renewable energy technologies such as solar photovoltaic and wind power are considered viable options in non-interconnected zones (ZNIs). Integrating sustainable sources into potable water generation and management processes is vital, and understanding how these systems can interact optimally is essential [3], highlighting the need for rational and efficient management and planning strategies [5].

In addition to these benefits, IWEMGs also stand out for their ability to provide a more reliable source of energy and water in remote areas where traditional infrastructure may be lacking. These microgrids enable communities to rely less on external energy sources, thereby improving their energy security and independence. By reducing dependence on costly energy imports and extensive infrastructure, isolated microgrids can result in significant cost savings for communities in isolated areas [6]. Implementing renewable energy technologies in these systems not only promotes environmental sustainability but also enhances access to clean and safe water sources [4]. Disaster resilience is another key benefit, as isolated microgrids can maintain the supply of essential services even in emergency situations [7]. This capacity to empower local communities to take control of their energy and water resources not only fosters self-sufficiency but also supports sustainable economic development [8]. The flexibility and scalability of these systems allow them to adapt to the specific needs of each community and expand as demand grows, promoting innovation and sustainable development in remote regions [9].

The published literature underscores the significance of certain developments implemented as management and planning tools in IWEMGs. However, a noticeable gap exists in the lack of models to optimize long-term water supply system planning while considering renewable energies [6]. Additionally, challenges and opportunities in integrated tool development are presented, addressing the high complexity and variable dimensionality in decision-making problems for optimal management [10]. The use of mathematical programming to develop and solve these issues is highlighted [6], with recent years witnessing the emergence of new techniques related to reinforcement learning, artificial intelligence, and machine learning, notably in smart electrical grids [9].

The primary challenges in generating and demanding water and energy resources lie in management, planning, and sizing approaches. Complications such as natural stochastic fluctuations, variability, and uncertainties are challenging to mitigate (e.g., noisy data or inaccurate measurements) [11]. Data from measuring variables related to water and energy generation and usage are crucial for forecasting, management, and planning tasks. Modern smart meters and remote sensors facilitate data acquisition with precision and acceptable resolution, while communication technologies enable the storage of large data volumes [12,13]. However, the limited data can pose challenges, such as accurately determining probability distributions; thus, obtaining historical data becomes relevant [14]. These databases, from which statistical parameters can be extracted, are instrumental in resource disaggregation and are a crucial decision-making tool when IWEMG infrastructure and resources are optimally allocated over planning horizons [15].

In this context, IWEMGs have been studied in recent years as a flexible and cost-effective method of supplying resources that generate welfare for remote communities [8]. This approach is particularly advantageous in various application environments sharing the challenge of accessing water and energy networks. Isolated, desert, and jungle communities exemplify these issues [7,16]. Therefore, cooperation between water and energy infrastructures is crucial for IWEMG operation, as for any study objective the two microgrids must be viewed as a single entity, necessitating the integration of all models, elements, conditions, properties, and constraints [17].

Our primary aim with this document is to apply a systematic methodology to analyze the recent literature about the key components, architectures, technological advances, and management and planning methods of IWEMGs. We propose a structured taxonomy to efficiently organize the existing literature and facilitate understanding of the current dynamics and challenges in this field. This approach intends not only to shed light on IWEMG management and planning strategies but also to encourage microgrid designers to integrate water–energy nexus considerations into their projects using an optimization framework. This study significantly contributes to the existing literature by:

1. Utilizing the water–energy nexus in IWEMGs to structure and synthesize the current state of knowledge in this field.
2. Introducing a simplified taxonomy covering:
    - Fundamental elements constituting the infrastructure of an IWEMG.
    - Formulation of optimization problems in management and resource planning models, as well as in the sizing of IWEMG infrastructure.
    - Solution methods applied to optimization problems formulated specifically for IWEMGs.
3. Assessing the most common computational design tools and examining their potential in the IWEMG context.

The document is organized as follows: The methods used in the document review are described in Section 2, the relevant elements and definitions in an IWEMG are located in Section 3, the types of optimization problems used in an IWEMG are explored in Section 4, the solution methods for an IWEMG's optimization problems are discussed in Section 5, and finally, in Section 6, conclusions are drawn, gaps in the state of the art of IWEMGs are raised, and future work is proposed.

2. Review Methods

In recent years, academia and industry have shown increasing interest in the relationship between water and energy via IWEMGs. Similarly, many research efforts have focused on management, planning, and sizing techniques. This paper performs full-text searches and standard summaries of the published literature over the past 10 years in order to conduct a comprehensive review and present the state of the art in this field. In this manner, the most pertinent research studies are compiled. For this research, the Web of Science (WOS) databases Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI), and Conference Proceedings Index Science (CPI-S) were selected. Similar information was obtained from Google Scholar; the data provided by these tools were useful for directing the search in other massive databases such as IEEE Xplore, ScienceDirect, SpringerLink, Taylor & Francis, and others.

Initially, we performed a targeted search of the aforementioned databases using terms such as "water and energy microgrids", "energy and water microgrids", "water-energy nexus", "isolated energy and water microgrids", and "isolated microgrids of energy and water". As a result, 322 articles were extracted from the databases. Figure 1 depicts the trend in the number of publications during the specified time interval. The number of publications increases up to the year 2020, after which it remains stable or even decreases. This effect may have been caused by the COVID-19 pandemic. After obtaining the basic information from the initial articles, we read the summaries to determine if they focus on water and energy microgrids that are isolated from the rest of the grid. Consequently, documents containing scant information on water and energy microgrids are removed. Due to their similarities with IWEMGs, articles containing information on water and energy microgrids connected to the electricity grid are not discarded. After this stage of filtering, the final sample consists of 94 articles published between 2014 and 2024.

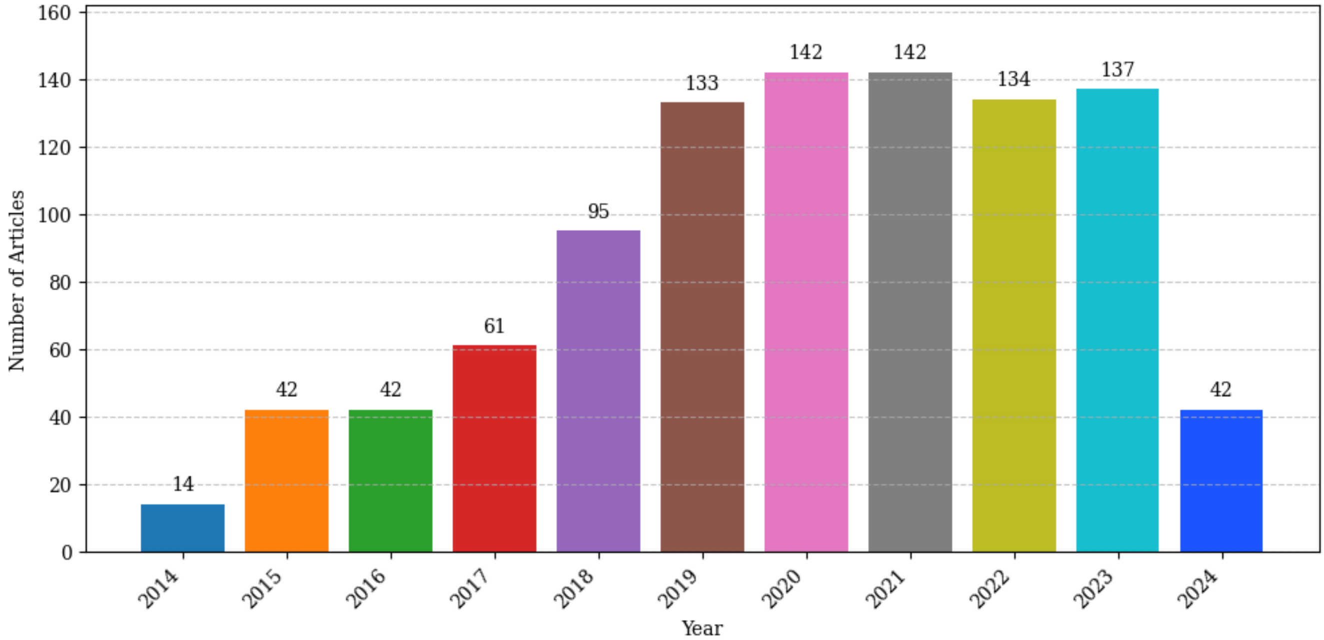

Figure 1. Research trend in water–energy nexus from 2012 to 2024.

The selected articles underwent a comprehensive review to distill the key concepts within the realm of water–energy microgrids. Based on their most significant characteristics, these articles were methodically classified into various categories for an in-depth examination. This document outlines Section 3 (description, elements, and concepts of an IWEMG), Section 4 (formulation of optimization problems in IWEMGs management and planning), and Section 5 (methods for solving IWEMG optimization problems) using the most relevant classification criteria established in our research. Following this rigorous selection methodology, our focus was exclusively on articles pertaining to isolated water and energy networks. As a result, 16 articles, published between 2014 and 2024, were identified as relevant to our study.

Additionally, Table 1 contains a list of references, the article type, and the principal contributions of each of the 16 publications. Sections 4 and 5 also use the information deposited there. Furthermore, it is important to note that among the chosen samples, only one review article pertaining to IWEMG was discovered. Therefore, in light of the challenges posed by the Sustainable Development Goals of the UN 2030 Agenda for Sustainable Development [1], it is anticipated that the number of publications concerning IWEMGs will increase in 2024.

Table 1. Main research studies in the area of planning and resource management in IWEMGs.

Ref Year	Type	Optimization Method	Key Findings	Application Area	Contributions/Impact	Experimental Platforms
[3] 2021	Journal	Mixed-integer nonlinear programming	Integration of a desalination module reduces peak demands by >30% with renewable sources and saline water.	Desalination, isolated microgrids	Proposes an optimization framework integrating desalination into microgrids.	Yes—Physical implementation
[8] 2018	Technical Report	Not specified	Identification of opportunities for water–energy microgrids and analysis of energy and water efficiency.	Water–energy microgrids, research	Detailed analysis at a test site, setting a model for future research.	Yes—Physical implementation
[17] 2020	Journal	Mixed-integer linear programming	Optimization of energy consumption in water–energy microgrids through the scheduling of tanks and pumps.	Water distribution systems	Develops an optimization model for energy efficiency in water systems.	Yes—Physical implementation
[18] 2011	Conference	Particle swarm optimization	Technical and economic evaluation of polygeneration microgrids to supply energy, water, and fuel.	Remote areas, polygeneration microgrids	Proposes and evaluates a microgrid design to meet diverse needs in isolated areas.	Yes—Physical implementation
[19]	Conference	Linear optimization	Optimal management model for water–energy microgrids with the goal of minimizing operational costs.	Isolated communities, microgrids	Management model optimizing operational costs in water–energy microgrids.	No—Simulation
[20] 2020	Journal	Multi-objective optimization	Cost evaluation for hybrid energy systems with integrated desalination using game theory.	Hybrid systems, desalination	Multi-objective approach to determine costs and optimize hybrid systems with desalination.	Yes—Physical implementation
[21] 2021	Conference	Mixed-integer quadratic programming	Joint optimization of water and power distribution networks to minimize energy consumption and losses.	Water and power distribution networks	Co-optimization of interdependent networks, improving efficiency and reducing losses.	No—Simulation
[22] 2020	Journal	Mixed-integer nonlinear programming	Co-optimization of water demand and energy consumption to maximize efficiency in isolated microgrids.	Isolated microgrids, energy efficiency	Co-optimization strategy to improve energy efficiency in water–energy microgrids.	No—Simulation
[23] 2017	Journal	Game theory with decentralized agents	Application of game theory to energy management in autonomous polygeneration microgrids.	Polygeneration microgrids, energy management	Uses game theory to improve management and cooperation in polygeneration microgrids.	Yes—Physical implementation
[24] 2018	Journal	Mixed-integer convex programming	Optimal demand management in the water–energy nexus using quasi-convex hull relaxation.	Water–energy nexus, demand management	Demand management model leveraging the water–energy relationship to optimize resources.	No—Simulation
[25] 2020	Journal	Mixed-integer nonlinear programming	Microgrid optimization through virtual electricity storage and deferrable power-driven demands.	Microgrids, virtual storage	Innovative approach to microgrid scheduling using virtual storage and deferrable demands.	No—Simulation
[26] 2017	Journal	Mixed-integer nonlinear programming	Modeling a micro-nexus of water and energy for co-optimization of water and energy networks.	Smart cities, micro-nexus	Proposes an integrated model of water and energy for applications in smart cities and buildings.	No—Simulation
[27] 2023	MIMO—predictive control	Predictive control for demand management	Interconnected microgrids, predictive control.	Control for management of interconnected water–energy microgrids.	Simulate environment, MATLAB.	No—Simulation
[28] 2023	Conference	MIMO-based predictive control	Predictive control strategy for demand management in isolated water–energy microgrids.	Isolated microgrids, predictive control	Applies predictive control for optimized management of isolated water–energy microgrids.	No—Simulation
[29] 2022	Conference	Stochastic programming	Stochastic optimization in water–energy microgrids for applications in arid zones.	Arid zones, stochastic optimization	Implements stochastic optimization for microgrids in arid zones, focusing on La Guajira, Colombia.	No—Simulation
[30] 2024	Journal	Game theory with decentralized agents	Integrated model composed of consumer agents, generator agents, and prosumer agents in IWEMs	Arid zones, water and power distribution	Use of game theory in the management of hydro-energy resources over a time horizon in an IWEMG.	No—Simulation

3. Description, Elements, and Concepts of an IWEMG

The main objective of an IWEMG is to meet water and energy demands while adhering to the system's inherent constraints. To achieve this, an IWEMG can be composed of several components that must be optimally integrated, including water and/or energy storage systems, multiple power generation systems (renewable and non-renewable), water generation systems (depending on needs and location), communication technologies, inter-system processing, and resource management methods [16,31]. The synergy between these diverse components emphasizes the critical nature of their interconnected functionality. Table 1 highlights the use of various experimental platforms in the study of IWEMGs. Several studies have implemented physical solutions, such as the integration of desalination modules and the technical and economic evaluation of polygeneration microgrids, allowing models to be validated under real conditions. These experiments provide valuable data and establish models for future research. On the other hand, some studies rely on simulations to test and optimize their models, using tools such as mixed-integer nonlinear programming and game theory. These simulations are crucial for developing and refining solutions before physical implementation. The combined use of both physical and simulated experimental platforms is essential for advancing the efficiency and sustainability of IWEMGs. The elements, systems, and units that can be part of an IWEMG are illustrated in Figure 2. Following this introduction, we will delve into the detailed descriptions of the main elements and explore the most important definitions and configurations of an IWEMG, along with a bibliographical review of the most relevant works presenting IWEMG topologies.

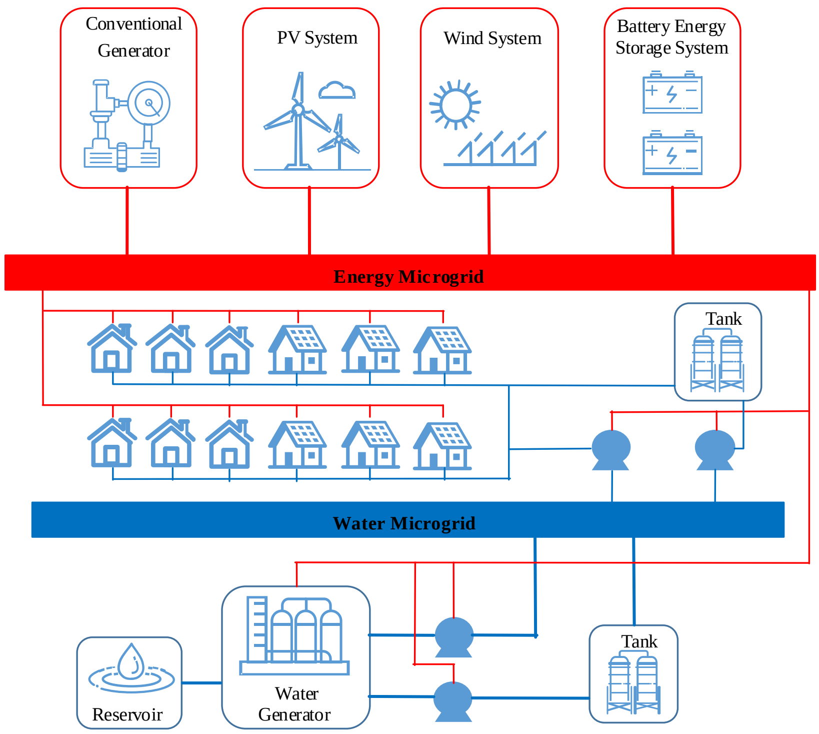

Figure 2. Schematic description of an integrated water–energy network.

3.1. Energy–Water Nexus

The nexus between water and energy is defined as a set of systems composed of two infrastructures: one with the necessary elements to form a complete energy value chain (activities necessary to create a service) and the other a water one [32]. Recently, the energy–water nexus has gained attention as a single interlinked system from policy, systems engineering and technical perspectives. This increasing focus underscores the importance of examining how energy and water infrastructures not only coexist but enhance each other's operational efficiency. While some works have developed holistic engineering system models [33,34], the primary focus of the literature has been to analyze and design individual energy–water couplings. The greatest attention has been given to the cross-interactions of energy supply with water demand or vice versa. Moreover, energy management has emerged as a crucial concern for utilities, particularly those that use electrical pumping energy to deliver water for residential, industrial, and irrigational purposes [32]. On the demand side, the residential commercial, and industrial use of electric heating and cooling for water consumption presents a major coupling [35]. The subsequent sections will build on this foundation, exploring how these interactions influence the design and functionality of IWEMGs.

The number of studies on the water–energy nexus has clearly increased, as has the scientific community's ability to productively assess water–energy interrelationships at higher resolution. Many studies aim to develop new methods for thoroughly assessing the interactions of water, energy, and other elements. Similarly, much research is in the "understanding" stage, with a focus on quantitative analysis of the water–energy nexus [36].

3.2. Energy Storage Systems for IWEMGs

Commonly, an IWEMG is powered by non-traditional renewable energy sources. The majority of these sources are intermittent, which presents a significant challenge in terms of power generation and load balance maintenance in order to ensure the stability and reliability of an electrical microgrid [37]. This intermittency necessitates robust solutions that can maintain consistent power and water supplies, highlighting the pivotal role of energy storage systems. Great efforts have been made to find viable solutions, such as electrical energy storage (EES), load switching via demand management, interconnection with external networks, and so on. EES has been identified as one of the most promising approaches among all possible solutions [37–39], providing a reliable buffer that enables the continuous operation of both power and water generation systems. A classification takes into account its primary energy source, so it is divided into five categories: electrical, mechanical, thermal, electrochemical, and magnetic [40].

At present, the most famous ESS in the world is the battery energy storage system (BESS) [41,42]. It is an electrochemical ESS that produces or absorbs electrical energy by means of a chemical reaction [43,44]. In addition to BESSs, some hydrogen-based generating units, such as some types of fuel cells, can be classified as chemical ESSs. In this case, the existence of the hydrogen reservoir offers the possibility of generating electricity when needed [39,45]. Pumped hydro storage power plants can be considered as energy-intensive ESSs that have been used in the power system for decades [37,46–48]. The flywheel energy storage system, FESS, is an electromechanical ESS that stores electrical energy in mechanical form. A round, low-friction moving disk stores electrical energy in kinetic form. There are two types of FESS: low speed and high speed [49–51], with high and low inertia disks, respectively. The compressed air ESS (CAESS) is a large-capacity ESS used in power systems [52,53]. This ESS stores air at times of low energy demand in large tanks. An ESS that stores heat in an insulated tank is called a thermal energy storage system (TESS) [54–56]. The stored heat can be used in the power generation process. Another solution for storing electrical energy is its storage in a magnetic field. Superconducting magnetic energy storage (SMES) stores electrical energy in a magnetic field generated by direct current [57,58].

Water storage systems, such as elevated tanks and reservoirs, play a crucial role in ensuring a stable water supply in IWEMGs. These systems can store excess water generated during periods of low demand or high availability, which can then be utilized during peak demand times or when water generation is low. Elevated water tanks, in particular, provide the added benefit of utilizing gravitational force to supply water without the need for additional energy input, thus enhancing the overall efficiency of the system [59,60]. This approach not only stabilizes the water supply but also integrates seamlessly with renewable energy sources, making it an ideal solution for remote and isolated communities.

Hydropumps and elevated tanks can also be integrated into IWEMGs as a form of mechanical energy storage. During periods of excess energy production, water can be pumped from a lower elevation to an elevated tank using renewable energy sources such as solar or wind power. This stored water can later be released through turbines to generate electricity when renewable energy production is low or when there is a high demand for power [61,62]. This method of energy generation not only provides a reliable backup power source but also helps in balancing the load and maintaining grid stability. Additionally, the use of hydropumps and elevated tanks leverages the natural topography and gravitational potential energy, making it a cost-effective and sustainable option for isolated microgrids [37,38].

These water and energy storage solutions, combined with advanced energy management systems, enhance the resilience and sustainability of IWEMGs, ensuring reliable access to essential resources in remote and isolated communities. By integrating these technologies, IWEMGs can achieve a higher degree of self-sufficiency and operational efficiency, which are critical for the long-term success and sustainability of these systems [37,40].

3.3. Drinking Water Generators in an IWEMG

Every year, new techniques for producing water that are more efficient, economical, and portable are introduced [6,63]. As we transition from discussing energy storage, it becomes clear that these innovations in water generation are equally essential. In general, seawater sweetening, polluted water treatment, wastewater recycling, and water production from air and fog are all water supply solutions that can be applied to an IWEMG [64]. This section will explore these technologies in detail, particularly focusing on how they integrate within the broader framework of IWEMGs to address the unique challenges of remote and isolated communities.

A desalination device essentially separates saline water into two streams: one with a low concentration of dissolved salts (the freshwater stream) and the other containing the remaining dissolved salts (the concentrate or brine stream) [65]. The device requires energy to operate and can use several different technologies for separation. Two basic technologies are used to remove salts from ocean water: thermal distillation and membrane separation. Industrial desalination technologies use semi-permeable membranes to separate the solvent or some solutes, or involve phase changes [66]. All processes require chemical pretreatment of the raw brackish water to prevent scaling, foaming, corrosion, biological growth, and fouling, and also require chemical post-treatment of the processed water [65,67]. Commercial desalination processes or conventional technologies for the treatment of water of impaired or marginal quality consist of separation of freshwater from saline water, simple sedimentation, and disinfection with chlorine or iodine. These include multi-stage flash (MSF), multiple effect (ME), vapor compression (VC), which can be thermal (TVC) or mechanical (MVC), reverse osmosis (RO), ion exchange, electrodialysis, phase change, and solvent extraction [67]. For optimal operation, the implementation of the aforementioned techniques necessitates the massive use of energy. The application of sustainable/renewable energy for water production is linked to the nexus between water and energy in desalination systems [64]. On the other hand, it is estimated that energy consumption accounts for 50% of the cost of desalination systems [68]. The advantages of desalination include its ability to provide large quantities of potable water from abundant sources like the ocean and the potential for integration with renewable energy sources to improve the sustainability of the process [64]. However, the disadvantages include high energy consumption and the environmental challenges associated with managing the concentrated brine byproduct [67]. Although it promises an inexhaustible source of water, operational and environmental costs can be prohibitive, limiting its applicability in certain regions. Additionally, reliance on external energy sources can increase the vulnerability of these systems during emergencies or energy infrastructure failures.

Wastewater recycling is a technique that allows for the treatment and reuse of used water for various applications, including agricultural irrigation, aquifer recharge, and industrial use. This process involves a series of treatment stages that may include filtration, disinfection, and biological treatment to remove contaminants and pathogens from the wastewater [66]. The benefits of wastewater recycling include reducing the demand on freshwater sources, improving water sustainability, and decreasing pollution of natural water bodies [65]. However, the challenges include high initial costs for the implementation and maintenance of treatment plants, as well as the need for constant monitoring to ensure the quality of the treated water [67]. While it reduces pressure on freshwater sources, negative public perception and high costs can hinder its large-scale adoption. Furthermore, the treatment of wastewater requires advanced technology and skilled personnel, which may not be available in all regions, especially in rural or developing areas.

Water production from air and fog is an innovative technique that utilizes devices such as atmospheric water generators (AWGs) to condense water vapor by cooling the air below its dew point [69]. These systems can be particularly useful in regions with high humidity and limited surface water resources. The benefits of this technique include its portability and the ability to generate potable water in remote locations without a pre-existing water source [70]. However, the challenges include high energy consumption, which can be a barrier in areas without reliable energy sources, and the variability in the amount of water generated depending on weather conditions [71,72]. Additionally, it is crucial to implement additional filtration stages to ensure the potability of the generated water [73]. Despite offering an innovative solution for remote areas, the reliance on favorable weather conditions and its high energy demand can limit its long-term viability. Moreover, the initial investment in advanced technology can be substantial, which could impede its implementation in communities with limited financial resources.

3.4. Renewable Energy for Desalination

Water generation technologies have seen tremendous improvements, but their widespread use remains limited, mainly because of the high energy needs that are currently met by fossil fuels [74]. Alternative energy sources are essential to meet the growing demand for water desalination [67]. In recent decades, many efforts have been made in the use of different renewable energy (RE) sources to run desalination processes [66]. However, most of these plants are connected to the power grid to ensure a continuous supply of energy for stable operation [75].

It is not easy to determine the most suitable renewable energy source (RES) for a water generation method, considering the efficiency and varieties of both RESs and water generation methods. According to [76], the choice of RES depends on several variables, such as the size of the plant, its location, the pressure and characteristics of the feed, and the expected cost of freshwater [77]. Limitations to the use of RESs are the inherent low intensity and intermittent characteristics of some of them [76,78]. These difficulties can be minimized or even eliminated by integration with the grid, hybridization, and the use of energy storage systems or batteries. Although [77] shows the potential integration of RES with desalination systems, no studies have been conducted to determine which renewable energy source is best for atmospheric water generation systems.

3.5. Topologies Proposed for IWEMGs in Research Articles

In this subsection, we present selected research papers that discuss the proposed general topology for an IWEMG. Table 2 provides information on relevant works that share similar elements and topologies with an IWEMG. These studies offer valuable insights into potential topologies that can be explored in future research. However, given the scope of this review, there is a predominant focus on articles that present topologies aligned with the structure of an IWEMG.

In [3], a topology is presented which includes a reservoir, two water storage tanks, 40 nodes, and six pumps that make up the water system, a hybrid electrodialysis–reverse osmosis desalination module, two battery storage units, two wind turbines, two sets of photovoltaic plants, and a conventional alternating current generator.

A similar topology is presented in [17], with the exception that a water generation system is not modeled. The behavior of the BESS is modeled as a bidirectional element, which can be computed as a load to provide a response to demand, and is also capable of storing excess energy to support demand peaks. The hydraulic network is made up of seven nodes, a tank, a pump, a reservoir and five home nodes, which fulfill the function of supplying the water demanded by each of the homes.

A comparable study is presented in [22]; the system consists of a microgrid, energy storage elements, conventional diesel, and natural gas electricity generators, plus renewable energy generators such as wind and solar, and a combined heat and gas plant. The water microgrid is made up of a water tank, six distribution nodes, and two pumps; a diurnal profile of water demand is also taken into account. In [79], the same author proposes the same topology above.

As a solution for supplying energy and drinking water in isolated microgrids, an energy polygeneration system in isolated microgrids is proposed in [18]. Photovoltaic panels, a wind turbine, a battery bank, a proton exchange membrane (PEM) fuel cell, a PEM electrolyzer, a metal hydride tank, and an energy recovery reverse osmosis desalination unit are all part of the microgrid.

The coupling between two networks is proposed in [21]; the networks are composed of pumps, photovoltaic panels, photovoltaic inverters in the power distribution networks, water storage tanks, and reservoirs.

A physical structure of two networks is considered in [24]. A distribution network, or microgrid, is integrated with renewable energy and a BESS on the electricity side. A network of pipes, pumps, utility-owned and customer-owned tanks, and irrigation systems comprise the water side. Water treatment facilities, including desalination, and electric vehicles (EVs) are among the loads considered.

The virtual electricity storage provided by distributed thermal/water demands is highlighted in [25]. The storage and distribution of drinking water using tanks and pumps are modeled. The system is made up of renewable energies in various nodes and conventional and flexible electrical loads. The microgrid includes battery storage.

A micro water–energy nexus is presented in [26]. Storage elements such as batteries, renewable energies, diesel generators, and energy demands are taken into account, along with water tanks and pumps.

The authors of [19,29] propose a scheme for a standalone water and energy microgrid composed of renewable energies, a water generator, a water and energy storage element via a hydro pump, and water and energy demands.

The authors of [20] propose a topology that is composed of a hybrid energy system that includes seawater desalination, as well as a diesel generator (DG) coupled to photovoltaic/thermal panels (PVTs) that provides electricity to the houses and the desalination system in this system (DS). The PVT panels also supply thermal energy, necessary to meet the cooling demand, through an absorption chiller (AC), which acts as an energy converter in the system. An electric chiller (EC) serves as a backup cooling system. The electrical storage system (ESS) and the thermal storage system (TSS) store excess electricity and thermal energy, respectively.

In [23], a topology of polygeneration networks is analyzed, composed of: electrolyzers, fuel cells, which are capable of interacting with each other, photovoltaic solar energy, a wind turbine, a proton exchange membrane fuel cell (PEM), a 48 V deep discharge solar lead–acid battery bank, and a water tank. In addition, household electrical consumption (e.g., lighting, refrigeration, kitchen appliances, etc.), and a reverse osmosis desalination unit are considered.

The analysis of research on integrated water and energy microgrids (IWEMGs) shows a wide range of system configurations that integrate renewable energy with water management to enhance efficiency and sustainability. This integration is crucial for improving the resilience of microgrids in isolated areas. The studies highlight the challenge of needing more advanced control mechanisms and smarter grid integration to manage the variability in renewable resources and water demands.

Future research should focus on developing advanced predictive algorithms and machine learning to dynamically manage system demands. Exploring new technologies like IoT sensors and blockchain could lead to more robust and autonomous IWEMGs.

Expanding these systems to larger grids or urban settings could increase their impact across different regions and socio-economic backgrounds.

Table 2 summarizes key elements from significant studies on IWEMGs, showing diverse configurations that reflect the integration of water and energy systems. It underscores the shift towards renewable solutions for long-term sustainability, marking progress in managing and optimizing these resources and pointing towards developing more efficient technologies.

Table 2. Elements present in the most relevant works related to IWEMGs.

Reference Year	Isolated Microgrids	Water Microgrids	Water–Energy Nexus	Desalination	Water Storage	Energy Storage	Renewable Energy	Energy Microgrids
[80] 2018			✓	✓	✓	✓	✓	
[32] 2014		✓		✓	✓	✓	✓	✓
[81] 2014		✓			✓	✓		✓
[82] 2020		✓	✓	✓	✓	✓	✓	✓
[83] 2021		✓	✓	✓	✓	✓	✓	✓
[84] 2020		✓	✓	✓	✓	✓	✓	✓
[85] 2019		✓	✓	✓	✓	✓	✓	✓
[86] 2019		✓	✓	✓	✓	✓	✓	✓
[87] 2018		✓	✓	✓	✓	✓	✓	✓
[88] 2020		✓	✓	✓	✓	✓	✓	✓
[31] 2022		✓	✓	✓	✓	✓	✓	✓
[89] 2014		✓	✓	✓	✓	✓	✓	✓
[90] 2016			✓	✓	✓	✓		✓
[16] 2014	✓			✓		✓	✓	✓
[91] 2020	✓				✓	✓	✓	✓
[92] 2020	✓		✓	✓	✓	✓	✓	✓
[93] 2020	✓		✓	✓		✓	✓	✓
[94] 2012	✓		✓	✓	✓	✓	✓	✓
[95] 2017	✓		✓	✓			✓	✓
[8] 2018	✓	✓	✓		✓	✓	✓	✓
[17] 2020	✓	✓			✓	✓	✓	✓
[96] 2020	✓	✓			✓	✓	✓	✓
[97] 2018	✓	✓		✓	✓	✓	✓	✓
[21] 2021	✓	✓	✓				✓	
[22] 2020	✓	✓	✓		✓	✓	✓	✓
[24] 2018	✓	✓	✓		✓	✓	✓	✓
[25] 2020	✓	✓	✓		✓	✓	✓	✓
[3] 2021	✓	✓	✓	✓	✓	✓	✓	✓
[23] 2017	✓	✓	✓	✓	✓	✓	✓	✓
[79] 2021	✓	✓	✓	✓	✓	✓	✓	✓
[18] 2011	✓	✓	✓	✓	✓	✓	✓	✓
[19] 2021	✓	✓	✓	✓	✓	✓	✓	✓
[20] 2020	✓	✓	✓	✓	✓	✓	✓	✓
[26] 2017	✓	✓	✓	✓	✓	✓	✓	✓
[30] 2024	✓	✓	✓	✓	✓	✓	✓	✓

4. Formulation of Optimization Problems in IWEMG Management and Planning

This section addresses various methodological approaches for formulating optimization problems applied to resource management, scheduling, and planning in IWEMGs. The selected documents detail procedures that facilitate system modeling and subsequent problem formulation, aimed at maximizing resource use efficiency within an IWEMG. Given the dynamic, nonlinear, and stochastic nature of water and energy supplies and demands in an IWEMG, integrated planning and management pose a significant challenge in optimization problem formulation. These problems critically depend on data related to the physical processes of the system, including generation and demand aspects [11]. System component modeling is particularly challenging due to distribution links involving interdependent water and energy variables and parameters within the framework of integrated management.

In the formulation of optimization problems for IWEMGs, it is feasible to consider multiple generation and storage technologies. This allows various parameters and control variables to define the degrees of freedom of the optimization problem, aimed at managing and planning the resources of the microgrid and its energy and water subsystems. The methods used must be interpretable and replicable, regardless of location constraints, to develop optimization models that generalize the performance of specific components within integrated multi-source power and water systems. On the other hand, considering characteristics observed in real-world applications, such as the use of binary variables and bilinear terms, there is a need to explore methods that effectively solve optimization problems and promote integrated management of water and energy systems [98]. Section 5 will address these methods in detail.

Within the context of the water–energy nexus applied to IWEMGs, addressing nexus issues could be achieved by formulating optimization problems independently for each sector. However, the specific formulation of these optimization problems depends on the system characteristics, the objective function, and the operating environment [99]. Therefore, optimization problems can be classified based on various criteria, including linearity, nonlinearity, non-convexity, mixed/integer nature, single/multiple objectivity, and stochastic/deterministic characteristics [6].

In current research on IWEMG management and planning methods, most optimization problems have been formulated as mixed-integer linear/nonlinear programs. However, other techniques have been explored that allow for significant results and conclusions. Therefore, in the subsections that follow, the formulation of an optimization problem is initially defined, and then, the mathematical methods identified in the bibliographic review are described, which have also been applied in the formulation of management and planning problems for IWEMGs.

4.1. Mathematical Optimization Problem Formulation

Mathematical programming plays a pivotal role in the simultaneous assessment of energy and water systems, facilitating their optimal integration. The design of these integrated systems, comparable to conventional optimization challenges in the hydro-energy sector, involves a mix of discrete and continuous variables. In both academic and practical applications involving integrated systems, methodologies can be differentiated based on the characteristics of the optimization problems they address. Given mathematical complexities such as nonlinearity and non-convexity, these optimization challenges are typically formulated using non-negative decision variables (x) in nonlinear (quasi/non)-convex and linear constraint ($f_i(x), h_i(x)$) and objective ($f_0(x)$) functions that define a feasible set ($\mathbb{R}_+^{nX} x \mathbb{Z}_+^{nX}$), e.g., Equations (1)–(5).

$$minimize \quad f_0(x) \tag{1}$$

$$Subject \quad to \tag{2}$$
$$f_i(x) \leq 0, i = 1, ...m \tag{3}$$
$$h_i(x) \leq 0, i = 1, ...p \tag{4}$$
$$x \in \mathbb{R}_+^{nX} x \mathbb{Z}_+^{nX} \tag{5}$$

Using the aforementioned standard model, a range of mathematical optimization techniques can be approached to address common problems. These approaches encompass mixed-integer linear programming (MILP), linear programming (LP), mixed-integer nonlinear programming (MINLP), and nonlinear programming (NLP). In the field of IWEMG management, determining the appropriate size, management and planning of resources is a fundamental task. Some studies have focused on optimizing the size of integrated water and power systems. However, these studies have ignored resource allocation issues while accentuating operational constraints, which are seen as seemingly simple but challenging when it comes to ensuring a reliable supply of water and power. To close this gap, it becomes imperative to incorporate resource allocation considerations into optimization problems related to management and planning. Thus, in the field of systems engineering and resource management, the optimization problem can be divided into two different substructures within a stipulated time frame (planning). By integrating the two tasks (sizing and allocation), the assessment tasks can be decomposed, facilitating analysis related to optimal sizing and allocation for water and power systems [99].

4.2. IWEMG Management Based on Nonlinear Programming of Mixed Integers and Nonlinear Programming

In the literature review related to IWEMGs, mixed-integer linear programming is the most commonly used technique for formulating optimization, management, and sizing problems. The nonlinear behavior of some elements that are part of an IWEMG, as well as their number and operational states, can be modeled in detail using nonlinear functions and binary variables.

The primary objective of the optimization problem presented in [3] is to reduce the energy consumption of the components within the water generation and distribution system, thereby lowering the overall energy generation costs. The objective function incorporates the cost functions of each generation unit, highlighting the use of the most economical energy resource based on electrical load and generator availability. Moreover, the water system model integrates fundamental constraints such as the mass conservation theorem and the Bernoulli equation, efficiently managing flows and valve states. A nonlinear co-optimization model is proposed that addresses optimal management in a hybrid water and energy system, considering the energy consumption of the water system as a constant load over 24 h, using a quadratic function for conventional energy generation, and adjusting the limitations of renewable energy systems based on environmental variables and their uncertainty, thus framing the entire system as a mixed-integer nonlinear optimization problem. This approach could be enhanced by integrating advanced meteorological predictions to further optimize the use of renewable resources.

In the study in [17], battery energy storage systems (BESSs) are modeled as bidirectional elements that respond to demand and store excess energy to manage demand peaks. The optimization considers the operational states of the pumps and analyzes residential water demand, integrating this information into the overall consumption of the hydro and energy system. The optimization strategy details the operation of pumps and tanks, taking into account physical properties such as pipe dimensions and flow rates, resulting in a model that optimizes energy consumption and ensures daily water demand. This model is innovative in integrating energy storage with water management, though its applicability may be limited in scenarios with high demand variability.

A related study in [22] delves into the modeling of pumps using quadratic functions to assess energy consumption under various flow and speed conditions. Three optimization scenarios are developed to compare efficiency: independent operation, integration with the conventional energy network without a storage element, and a fully integrated system with an energy storage unit. This mixed-integer nonlinear programming approach aims to minimize the energy consumption of the pumps over a full 24-h operational cycle. The analysis is notable for its comparative approach, suggesting the potential for including long-term cost and sustainability analyses.

The purpose in [79] is to strategically locate water pumps/turbines to maintain constant pressure and maximize energy generation. Operational constraints are modeled using quadratic functions, and both energy and mass conservation within the water network are considered. Moreover, a co-optimization model of an integrated water and energy system is developed, which includes conventional, solar photovoltaic, and wind generation units, some of which are nonlinear, as well as battery storage units. This co-optimization problem aims to minimize the costs of energy storage and generation units, thus enhancing energy efficiency, although exploring the environmental impact of large-scale implementation would be beneficial.

In [18], the system is described as a multidimensional, non-convex, nonlinear, and multimodal problem with binary variables, using data and simulations from previous works to derive component models. The objective function, which minimizes investment and maintenance costs over a 20-year period, identifies the most cost-effective system that can also meet all the system's needs at every time step. This research provides a solid foundation for strategic financial decisions; however, it faces the challenge of computational complexity due to the large amount of data processed.

In the work presented in [21], optimization of combined water and energy flow problems is addressed through collaborative resource management across distribution networks, emphasizing the interaction between water and energy networks. This integrated management aims to minimize both the energy consumption of pumps and active power losses. The complex nature of the problem, exacerbated by non-convex constraints arising from hydraulic dynamics, necessitates transforming the original problem into a convex one through successive linear approximations, ultimately formulated as quadratic programming with quadratic constraints and mixed integers, with the goal of minimizing active power losses in the energy distribution network. Although the study provides an innovative approach to resource management, the practical applicability of the solutions may be limited by the complexity of the required transformations.

The authors of [24] develop a multi-period mathematical model and design optimization algorithms for optimal resource allocation. This model integrates nonlinear equations for storage units and adapts assumptions for the water distribution network and its pumps, despite their inherent quadratic behavior, proposing them as linear. Moreover, constraints are specified to facilitate the connection between the water and energy networks, with the ultimate goal of reducing the total cost of energy required to meet the demands for electricity and water. The interdisciplinary approach to co-optimization is promising, but simplifying the dynamic behaviors of the pumps may not capture all the real system dynamics.

In [25], the study explores how variable water and temperature demands provide flexibility for adjusting significant electrical loads, enabling optimal energy distribution and improved electrical grid planning. It is assumed that water load flows are flexible, supported by users' own storage capabilities, which allows for considering lossless water storage solutions as economically viable options for optimizing the operation of the electrical system. Battery storage modeling is conducted using nonlinear equations, and an optimization approach is proposed to manage storage over the short and long terms, thereby minimizing the costs of electrical energy. This work ingeniously addresses the interaction between water demands and energy management, though it could benefit from a more detailed analysis of the long-term efficacy of lossless storage.

In [26], the study describes integrated systems of microgrids and water distribution, both directly connected to consumers. The models for both systems are high-fidelity nonlinear networks that use binary variables and mixed integers to describe the interactions and functionality of the system. The objective function of this co-optimization problem aims to minimize the cost of energy generated and consumed by the pumps, thereby optimizing resource scheduling over time. Although this approach provides a detailed and directly applicable methodology, the complexity of high-fidelity models may pose significant challenges in terms of computation and scalability in broader implementations.

In summary, the use of mixed-integer nonlinear programming (MINLP) in formulating optimization problems in IWEMGs is evident in the studies mentioned. This technique is particularly prominent in planning and management applications due to its ability to model all components of the systems with precision. However, challenges may arise in some instances due to the time required to process a large volume of data.

4.3. IWEMG Management Based on Linear Programming

In isolated water–energy microgrids, certain components are modeled using linear equations. It is essential to use first-order equations to establish the constraints and the objective function in the formulations. Additionally, linearization techniques are employed to determine operational points or to segment nonlinear equations, thus facilitating the management of the inherent complexity of these systems. However, while useful, linearization techniques may oversimplify the models of IWEMGs, potentially omitting critical system dynamics.

According to the studies in [19,29], the elements of IWEMGs are modeled using linear equations based on the principle of conservation of mass and the physical constraints of the components. In [19], water and energy demands are treated as constants, while the hydro-pump storage element serves as a link between the water and energy networks. The objective function in [19] aims to minimize the operational costs of producing water per cubic meter and the costs of its storage, managing resources within a seven-day framework. In contrast, [29] assesses two scenarios, one deterministic and the other stochastic, both structured in two stages. The objective function aims to minimize the installation of renewable energies in the first stage and the amount of water generated in the second stage, considering variations in demand and renewable energy generation. The comparison of deterministic and stochastic approaches in [29] provides valuable insight into uncertainty management, though further exploration of the interactions between the optimization model stages could deepen our understanding.

In [20], a linear programming technique is introduced for the multidimensional analysis of preferences. Two objective functions are defined: the first aims to minimize the economic costs of capital, fuel, and maintenance, while the second focuses on enhancing environmental protection. The conflicting nature of these objectives drives the need for multi-objective optimization to effectively balance both goals. This multidimensional approach highlights the complexity of balancing economic costs with environmental benefits, a key challenge in sustainability.

The use of linear programming in IWEMGs, due to the simplicity of the models and their rapid simulation, emerges as an appealing solution for system design and testing. However, although these systems can be developed and tested quickly, the final results often lack accuracy, which is crucial in contexts with high uncertainty. The speed and simplicity of linear programming are beneficial, but the compromised precision may limit its utility in critical applications where uncertainty plays a fundamental role.

4.4. IWEMG Management Based on Game Theory

This formulation method provides a mathematical framework for modeling and analyzing scenarios with multiple decision-makers, where each participant aims to achieve their objectives through strategic decisions [100]. Therefore, this technique is well-suited for management and planning models in IWEMGs. However, the formulation must be carefully customized to capture the complexity of real interactions.

In [23], the components are modeled using linear and quadratic equations, as seen with batteries or desalination agents. One objective function seeks to maximize the input from fuel cell and battery agents. Game theory is employed to formulate the energy management problem, simulating the array of strategies used by two players/agents in either a cooperative or non-cooperative power control game. To achieve optimal energy management and control of the microgrid's operations, the model relies on the level of energy produced by renewable sources and the energy stored in the battery bank. Nash equilibrium is utilized to reconcile the agents' objectives by maximizing their preferences, making the application of game theory in this context innovative. However, the complexity and computational requirements may limit its practical application.

The study presented in [30] explores the integration of renewable energies into water systems in isolated communities using an IWEMG model based on game theory. Consumers, producers, and prosumers engage in a non-cooperative game (Cournot competition) to optimize resource allocation. Implemented in Ranchería, La Guajira, Colombia, the model has proven effective in meeting local water and energy demands, supported by quantitative results that facilitate informed decision making. Despite its proven effectiveness, the model faces challenges in adaptability to dynamic changes, highlighting the need to explore its scalability and adaptability in different cultural contexts to ensure its global effectiveness. This approach represents a significant advancement in sustainable resource management and proposes a viable path for the development of policies and strategies for global implementation. The model is promising for the sustainability of isolated communities but must be better adapted to local and global variable contexts.

The advantages of the game theory approach to energy management are utilized to investigate the optimal solutions of games using Nash equilibrium. However, due to its complexity and high computational demands, it is a technique that has not yet been sufficiently explored in IWEMGs. While promising, the application of game theory in IWEMG management requires further exploration and simplification for broader adoption.

5. Methods for Solving IWEMG Optimization Problems

Mathematical models and algorithms are crucial for optimizing resource allocation, sizing, and scheduling decisions in isolated water–energy microgrids. Beyond conventional mathematical programming, heuristic and metaheuristic algorithms provide versatile alternatives for addressing IWEMG optimization challenges. Techniques such as genetic algorithms, particle swarm optimization, simulated annealing, and ant colony optimization are particularly adept at managing complex and nonlinear problems where exact solutions are elusive due to their capability to explore vast solution spaces effectively.

Given the inherent uncertainties in water and energy supply and demand, stochastic programming techniques are instrumental in IWEMGs. These techniques leverage probability distributions or scenario-based approaches to accommodate uncertainties, thereby facilitating the development of solutions that are both robust and reliable. This approach is particularly beneficial in planning under conditions of uncertainty, ensuring that solutions remain viable under various possible future scenarios.

IWEMG optimization frequently entails navigating through multiple conflicting objectives, including cost minimization, system reliability, and environmental impact. Multi-objective optimization methods, such as multi-objective evolutionary algorithms and Pareto optimization, are employed to discover trade-off solutions that balance these goals. These methods allow stakeholders to explore a spectrum of optimal solutions, aiding in decision-making processes that consider a broader range of outcomes.

The selection of an optimal method for solving an IWEMG problem depends heavily on the specific characteristics of the system, the defined objectives of the optimization problem, and the quality and quantity of available data. Understanding the computational tools, solution procedures, and algorithms used is essential due to the complexity of these problems. Table 3 outlines these aspects along with other pertinent characteristics of research in the field of IWEMG management and planning. The following subsections will delve deeper into each of these methods, examining their applications and benefits in the context of optimizing IWEMG operations.

Table 3. Summary of relevant characteristics in the selected articles on optimization for IWEMGs.

Ref	Problem Formulation	Procedure	Algorithm/ Solver	Tool	Objective
[3]	MINLP	Mathematical programming	BONMIN	MATLAB®, OPTI Toolbox	Minimize the costs of electricity generation from dispatchable distributed generation units.
[8]	MILP	Mathematical programming			Coordinated operation, maximum economic efficiency.
[17]	MINLP	Mathematical programming	BONMIN	MATLAB®, OPTI Toolbox	Minimize energy consumption and daily energy costs in WEMG.
[18]	MINLP	Heuristic	PSO	TRNSYS® 16, GenOpt® 2.0, TRNOPT®	Minimize the cost of investment and maintenance for a period of 20 years.
[19]	LP	Mathematical programming	CPLEX	GAMS Studio® 1.16.4	Minimize operating and production costs.
[20]	MINLP	Evolutive	Genetic algorithm (NSGA-II)	MATLAB®	Maximize environmental protection performance and minimize its economic cost.
[21]	MINLP	Mathematical programming	SDPT3, SeDuMi, MOSEK	MATLAB®, CVX Toolbox.	Minimize active power losses and energy consumption.
[22]	MINLP	Mathematical programming	BONMIN	MATLAB®, OPTI Toolbox	Minimize energy consumption.
[23]	MINLP	Game theory—intelligent agents	PSO	TRNSYS®, MATLAB®, GenOpt® 3	Maximize profits and achieve optimal energy management and control of the microgrid operation.
[24]	MINLP	Mathematical programming	Branch and Cut	Gurobi®	Minimize the total energy cost for meeting the demands of both electricity and water microgrids.
[25]	MINLP	Mathematical programming	BONMIN		Minimize costs and maximize the use of renewable energy.
[26]	MINLP	Mathematical programming			Minimize the energy consumption and total energy cost.
[79]	MINLP	Mathematical programming	BONMIN	MATLAB®, OPTI Toolbox	Maximizes the energy generation of pumps-as-turbines. Minimize the cost of energy generation in WEMG systems.

This section aims to clarify the methodologies and their applications within the scope of IWEMG, providing a comprehensive overview that may assist academics and practitioners in selecting the most appropriate optimization techniques based on specific project needs and constraints.

5.1. Exact Mathematical Methods

Mathematical algorithms based on exact and precise techniques, commonly referred to as standard mathematics, are routinely applied to resolve optimization issues in water and energy systems. These techniques typically start by calculating a lower bound and proceed by solving a convex relaxation of the original problem at each iteration. Simultaneously, an upper bound is calculated, and the relaxed variables are rounded to determine the optimal points of the original problem; this process is known as the branch and limit technique [101]. Mathematical procedures often delve into the structure of the optimization problem, incorporating common heuristics, pattern exploration, and robust statistical estimates based on empirical data [102].

Decomposition methods segment complex optimization tasks into manageable subproblems [102,103], traditionally termed as master/slave [104] and primal/dual [105] structures. Classical decomposition approaches like primal/dual [106] and mathematical techniques such as Benders decomposition [101] are employed to derive global bounds on objective values. Iterative algorithms such as branch and limit [101], cutting plane [107], and other reformulation-based mathematical algorithms are essential for optimizing the water–energy system. Additional solution methodologies include interior point [108,109] and Newton methods [110], which provide precise or nearly optimal solutions [111] for master–slave problems [112] and previously decomposed subproblems. Conventional solvers in mathematical programming frequently utilize iterative algorithms, like the cutting plane method [113], to secure exact or near-optimal solutions [114], thus defining lower or upper bounds that identify gaps in global optimization [115].

In [3,22,25,79], optimization problems are tackled using the BONMIN algorithm and the OPTI toolbox in MATLAB. The Open-Source Basic Nonlinear Mixed Integer Programming algorithm (BONMIN), an experimental C++ tool, addresses general mixed-integer nonlinear constraint problems. When dealing with convex objective functions and constraints, BONMIN provides precise solutions [116]. The BONMIN suite includes various algorithms:

- B-BB is an algorithm that uses the branch and bound technique and is based on NLP.
- B-QG is an implementation of the Quesada and Grossmann branch and cut algorithm.
- B-Hyb is a hybrid branch and cut algorithm based on an external approximation.
- B-OA is an algorithm that uses external approximation decomposition.

In [17], models are initially linearized to transform the MINLP problem into an MILP problem using the piecewise linear approximation for univariate functions [117] and the Big M method for bivariate functions. As model complexity increases, so does the number of binary variables and the arbitrary value of M [118], enhancing model accuracy but also extending computation time. All models are solved using the "OPTI" solver in the MATLAB® software.

Similarly, in [21], an MINLP problem is approached initially via monomial approximation [119] followed by the Big M method for modeling pump head loss constraints. The optimization is executed using a convex optimal water power flow (C-OWPF) algorithm designed for non-convex co-optimization, with solutions processed using the MATLAB® CVX-based optimization toolbox in conjunction with the Gurobi mixed-integer solver [120]. Gurobi Optimizer is renowned for its advanced capabilities in mathematical programming, optimized to leverage modern computing architectures and multicore processors with the latest algorithmic implementations [121].

5.2. Dual Derivation and Reformulation Methods

The quasi-convex hull relaxation method, recognized for its computational efficiency, is frequently employed to address the challenges posed by computationally intractable mixed-integer nonlinear programming (MINLP) problems. This method simplifies optimization tasks by replacing non-convex constraints with their convex or quasi-convex hulls, as detailed in [24,122]. The appeal of the convex hull lies in its ability to encompass the endpoints of the original non-convex set, facilitating the location of optimal solutions, typically at the extreme points of the convex hull, particularly when the objective function exhibits monotonic convexity within this region [123,124].

However, accurately determining the convex hulls for many non-convex sets remains a formidable challenge. In such scenarios, constructing a convex internal approximation of a non-convex set presents a viable alternative [125]. In the realm of MINLP, integer variables are typically confined to linear constraints. When dealing with intractable issues such as optimal water–power flow [126], the relaxation of quasi/non-convex constraints and objectives—either weakly or strongly—allows for the derivation of approximate solutions based on semi-definite mathematical properties. Moreover, for complex optimization problems that involve discrete and/or continuous variables along with bilinear terms, non-convex and nonlinear model equations are effectively handled by incorporating auxiliary variables and additional constraints.

Dual formulations derived from primal optimization problems facilitate the reframing of nonlinear multi-stage programs, aiming to enhance the robust operation of systems and interconnecting components within energy and water distribution networks [122]. In instances where technoeconomic or environmental objectives diverge significantly between primal and dual formulations, the dual function may exhibit non-differentiability at its optimum [127]. Utilizing Lagrange multipliers to reconceptualize an original non-convex problem helps uphold convexity properties under weak/strong duality theorems [128], which proves indispensable for critical sizing and scheduling tasks in power and water systems. For complex nonlinear optimization issues related to the capacity expansion planning of integrated power and water systems, leveraging convex relaxations not only enhances computational efficiency but also ensures solution accuracy [112,129]. This transformation of intractable optimization problems into manageable convex programs, such as mixed-integer programs [130], facilitates robust and multi-objective optimization strategies that adeptly manage the inherent uncertainties in water and energy supply and demand [131].

In [24], it is proposed that transforming a mixed-integer problem within the MINLP framework into a more computationally manageable mixed-integer configuration can significantly improve efficiency. Here, integer variables only appear in linear constraints. The Gurobi solver is employed to effectively address this problem. Furthermore, the relaxation method is also utilized in [25], where the system is modeled with differential equations incorporated into constraints, and the direct Euler method is applied to discretize these differential equations into linear equations due to constant parameters. Both BONMIN and Gurobi solvers were deployed in this investigation, illustrating a comprehensive approach to handling complex computational tasks.

The use of advanced dual derivation and reformulation methods in optimizing water–energy systems significantly enhances the handling of complex optimization tasks in mixed-integer nonlinear programming (MINLP). Techniques like the quasi-convex hull method simplify these challenges by transforming non-convex constraints, improving computational efficiency and solution feasibility. Despite progress, modeling accuracy and system complexity remain as challenges. The integration of sophisticated solvers and robust optimization strategies continues to advance the management of supply and demand uncertainties, driving towards more sustainable and reliable infrastructure solutions.

5.3. Stochastic Optimization

The deterministic and stochastic linear programming problems discussed in [19,29] were effectively resolved using the general algebraic modeling system (GAMS) with the CPLEX algorithm. CPLEX is adept at solving LP problems by employing a variety of algorithms, with the dual simplex algorithm often being the most efficient for most LP scenarios. Depending on the specific problem characteristics, alternative algorithms like the primal simplex, network optimizer, barrier, or sieve algorithms may be utilized. CPLEX also offers a concurrent mode, which leverages multiple algorithms simultaneously to solve problems, with the solution from the fastest algorithm being adopted. One notable challenge in solving large linear programming problems is the substantial memory requirement. Although CPLEX is designed to manage memory efficiently, physical memory limitations can still pose issues, leading to automatic adjustments that might compromise performance [132].

As computational resources continue to evolve, the efficiency of algorithms like CPLEX is increasingly enhanced through improvements in parallel processing and memory management techniques. These advancements allow for the handling of larger datasets and more complex model formulations without compromising computational speed or accuracy. Furthermore, ongoing developments in algorithmic strategies are aimed at reducing the memory footprint and improving the scalability of solutions to accommodate the growing size and complexity of linear programming problems in diverse fields such as logistics, finance, and engineering. These enhancements ensure that modern solvers not only provide accurate solutions but also adapt to the constraints of contemporary computing environments.

5.4. Heuristic and Evolutionary Methods

These algorithms represent advanced techniques employed to derive approximate yet feasible solutions for complex mathematical optimization problems, notably in domains such as integrated planning of water and energy systems [122,133]. Inspired by natural processes and competition, algorithms like evolutionary strategies [134], artificial bee colonies [135], colonial competition [136], particle swarm optimization [137], and non-dominated genetic classification [138] prove effective for such tasks. These techniques yield feasible and nearly optimal solutions, beneficial for both original and reformulated problems aimed at optimizing integrated energy and water systems. While traditional mathematical programming has its merits, these heuristic techniques offer robust alternative solutions and support comprehensive decision-making frameworks for energy and water system optimization [139].

The particle swarm optimization (PSO) metaheuristic algorithm, renowned for its global optimization efficiency for both continuous and discrete variable problems, is employed to solve problems as indicated in [18,23]. PSO is celebrated for its simplicity, minimal parameter tuning, and adaptability to constraints via penalty methods, yet it remains highly sensitive to parameter settings [140]. The system's design integration between TRNSYS®, a dynamic simulation software ideal for handling complex systems through FORTRAN subroutines, and GenOpt®, an optimization software that minimizes cost functions using external simulations, exemplifies a synergistic approach enhancing both simulation and optimization [18]. This integrated approach not only optimizes computational resources but also enhances the accuracy and efficiency of solving complex multi-variable optimization problems.

NSGA-II, a prominent metaheuristic optimization algorithm, is utilized for multi-objective optimization challenges, as demonstrated in [20]. An evolution from its predecessor NSGA [141], NSGA-II incorporates improvements such as elitism and the elimination of the need for a diversity-preserving sharing parameter, optimizing diversity via the crowding distance operator [142]. This makes NSGA-II not only computationally efficient but also effectively addresses the limitations of the original NSGA, maintaining a computational complexity of at most (MN^2). The utilization of NSGA-II within MATLAB's optimization toolbox for co-generation system design illustrates its capacity to identify optimal solutions efficiently, showcasing its viability for complex engineering applications.

6. Discussion and Future Perspectives

This section analyzes the prevalent methodologies in resource management and the optimal planning of microgrids, emphasizing the elements that integrate an IWEM and the inherent characteristics of the environment. As outlined in the problem formulation segment, the predominant approach involves mixed-integer nonlinear programming (MINLP). This technique models microgrid components using nonlinear functions, such as pumps, with binary variables indicating operational states and integer variables assigned for component initiation or installation. Although some studies leverage linear programming due to its simpler problem formulation, it remains instrumental in resource management, strategic planning, and estimating system capacities. Additionally, it adeptly handles uncertain parameters or distinct probability distributions, with processing speed contingent upon the volume of parameter data and the designated planning horizon.

The linkage between management systems and water storage systems, such as elevated tanks and reservoirs, with renewable energy sources like solar photovoltaic and wind power, is vital for IWEMGs. This integration not only improves efficiency and sustainability but also addresses resource management and strategic planning more holistically. These systems provide reliable water and energy supplies, leveraging gravitational force for efficient water distribution, and enhancing the overall sustainability of the system. This synergy not only stabilizes the water supply but also integrates seamlessly with renewable energy sources, making it an ideal solution for remote and isolated communities. The combined use of both physical and simulated experimental platforms is essential for advancing the efficiency and sustainability of IWEMGs.

A prominent trend in solving optimization challenges within microgrids involves exact methods, traditionally known as mathematical methods. These approaches are favored for their capability to reliably secure global solutions for convex problems (linear or quadratic) within a limited series of iterations. They achieve convergence without substantial reliance on convergence constants. Moreover, the termination criteria of these methods provide an optimality certificate by iteratively pinpointing exact or near-optimal solutions, gauging the global disparity between the lower and upper bounds of the objective values. While exact methods depend on the convex nature of mathematical properties for computationally feasible solutions within polynomial time, they face limitations in addressing non-convex (discrete/mixed-integer) challenges where computational demands may surge exponentially in large-scale implementations. Nonetheless, the diverse models available for each component of an integrated water and energy microgrid system (IWEMG) make these methods valuable for strategic management and planning. The efficacy, benefits, and limitations of these methods in the context of IWEMGs have been comprehensively documented.

To address intractable optimization issues, this paper introduces heuristic and evolutionary methods. These approaches manage non-convexities (e.g., bilinear terms) through practical reformulations, such as introducing binary auxiliary variables, facilitating the discovery of global solutions akin to those obtained using non-heuristic, exact methods. These strategies enable quicker convergence to optimal conditions within a finite number of iterations and are particularly effective for complex optimization challenges with combinatorial elements, offering computationally efficient, approximate, or nearly optimal solutions. However, when addressing scalable real-world scenarios, meticulous analysis of mathematical properties is crucial to achieve tight bounds on target values for optimal global convergence. Despite the feasibility of solutions derived from heuristic methods, including metaheuristic techniques like evolutionary algorithms that methodically avoid local optima, these approaches do not guarantee global optimization.

Additionally, the integration of game theory with intelligent agents is proposed as an innovative framework for addressing management and planning challenges in IWEMGs. This novel approach, although explored in limited studies, underscores the potential for integrating advanced machine learning techniques and new computational methodologies in optimizing IWEMG-specific issues, paving the way for future research and applications in this field.

7. Conclusions

The analysis of methodologies in resource management and optimal planning within microgrids predominantly relies on mixed-integer nonlinear programming (MINLP). This method utilizes binary and integer variables to dynamically model microgrid elements, demonstrating its effectiveness, especially when combined with linear programming. Although linear programming offers less detailed formulations, it remains crucial for integrating uncertain or probabilistic parameters, effectively managing resources and planning capacities.

Building on this foundation, exact methods enhance the modeling framework by leveraging the mathematical properties of convexity. These methods provide reliable solutions for convex problems and effectively address non-convex issues, albeit potentially increasing computational demands in large-scale scenarios. The comprehensive documentation and widespread use of these methods in IWEMGs highlight their significant role in strategic management and planning.

The transition from traditional to innovative approaches sees heuristic and evolutionary strategies emerge as robust alternatives. These strategies adeptly manage non-convexities through tactical reformulations, enabling the discovery of global solutions and accelerating convergence to optimal conditions. Particularly beneficial for complex tasks involving combinatorial elements, these strategies offer computationally efficient, approximate, or near-optimal solutions. However, their practical application in real-world scenarios requires rigorous analysis to ensure precision and swift global convergence, maintaining the integrity of results across scalable projects.

The introduction of game theory combined with intelligent agents marks a novel progression in this field. This innovative strategy, explored preliminarily, opens potential pathways for integrating advanced machine learning techniques and emerging computational methods into optimization processes tailored for IWEMGs. This forward-looking approach promises to enhance the strategic capabilities of microgrid management and planning, establishing a dynamic course for future research and practical applications.

Furthermore, the integration of water storage systems, such as elevated tanks and reservoirs, with renewable energy sources like solar photovoltaic and wind power, presents an interesting solution for IWEMGs. These systems provide reliable water and energy supplies, reinforcing efficient water distribution and improving overall system sustainability. This synergy and the water–energy nexus not only stabilize the water supply but also seamlessly integrate with renewable energy sources, making it an ideal solution for remote and isolated communities.

In summary, the integration of sophisticated modeling techniques, including MINLP, exact methods, heuristic strategies, and game theory, forms a robust framework for the efficient management and planning of IWEMGs. The combination of these methodologies ensures a comprehensive approach to addressing the complexities of resource management in microgrids, paving the way for future advancements in the field. As research progresses, focusing on the integration of renewable energy sources and advanced computational methods will be crucial for achieving sustainable and efficient microgrid systems.

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Abbreviations

The following abbreviations are used in this manuscript:

IWEMG	Isolated water and energy microgrid
ZNIs	Non-interconnected zones
WOS	Web of Science
SCIE	Science Citation Index Expanded
SSCI	Social Sciences Citation Index
CPI-S	Conference Proceedings Index Science
MIMO	Multiple input, multiple output
EES	Electrical energy storage
BESS	Battery energy storage system
CAESS	Compressed air ESS
TESS	Thermal energy storage system
SMES	Superconducting magnetic energy storage
MSF	Multi-stage flash
ME	Multiple effect

VC	Vapor compression
MVC	Mechanical vapor compression
TVC	Thermal vapor compression
RO	Reverse osmosis
AWG	Atmospheric water generator
RH	Relative humidity
TEC	Thermoelectric cooler
RES	Renewable energy source
PEM	Proton exchange membrane
EV	Electric vehicle
DG	Diesel generator
PVTs	Voltaic/thermal panels
DS	Desalination system
AC	Absorption chiller
EC	Electric chiller
TSS	Thermal storage system
PEM	Proton exchange membrane
MINLP	Mixed-integer nonlinear programming
MILP	Mixed-integer linear programming
LP	Linear programming
C-OWPF	Convex optimal water power flow
GAMS	General algebraic modeling system
PSO	Particle swarm optimization
NSGA-II	Non-dominated sorting genetic algorithm II

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