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Artificial intelligence application to the nexus of renewable energy, water, and the environment

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12.1 Introduction

In recent years, the rising number of extreme weathers caused by global warming due to increased carbon emissions from various sectors has posed a considerable threat to the survival and safety of humans (Jafarinejad et al., 2021; Liu, Xing, et al., 2022; You et al., 2023; Zhou & Liu, 2023). The science-based rational nexus of renewable energy (RE), water, and environment (REWE) is essential for sustainable development and carbon neutrality to decrease the occurrence of these disasters (Majeed & Luni, 2019). With the increase in population, the change of climate, and rapid urbanization processes, it becomes more difficult to predict future energy consumption, water use, and environmental changes in terms of their nexus. Extreme climatology events (e.g., floods and droughts) have occurred more frequently under climate change, which strongly affects the regeneration of RE and water resources (Zhou, 2023a, 2023b). For instance, extreme droughts have largely affected the production of energy due to the lack of available water for power generation plants (Luskova et al., 2018; Van Vliet et al., 2016). Thereby, there is an increase interest in exploring the REWE nexus (Zaidi et al., 2018).

In the last decade, many researchers have conducted research in modeling individual RE or water resource systems (Eftelioglu et al., 2016; Halstead et al., 2014). Regarding RE, the studies mainly focus on the integration and optimization of solar energy (He et al., 2021; Zhou, 2022c), geothermal energy (Liu et al., 2023; Liu, Qian, et al., 2022; Zhou et al., 2022), wind energy (Msigwa et al., 2022), and their applications with energy storage systems (Zhou et al., 2020, 2021). Compared to other RE sources, geothermal energy refers to energy sources that are contained underground and generally have more consistent thermal properties (Liu, Sun, et al., 2019; Liu et al., 2017; Liu et al., 2019; Qin et al., 2021). With the purpose of making more accurate and reliable predictions to support decision-making, investments, and planning on energy and water resources, different modeling approaches are adopted for simulating and forecasting the nexus of water and energy resources.

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These modeling approaches can be classified as process-based or data-driven-based. The process-based modeling approach is based on mathematics that provides a detailed representation and interpretation of the underlying physical processes between variables within a system through scientific principles (Oyebode et al., 2014). Concerning the advantages of the process-based modeling approach, it can increase the validity and utility of models because they are based on the physical processes within the system (Oyebode et al., 2014; Solomatine & Ostfeld, 2008). However, the process-based modeling approach is usually highly computationally expensive, and it has uncertainties in parameterization and calibration (Oyebode et al., 2014). Qiu et al. (2021) indicated that the process-based models have large uncertainties in prediction, especially concerning spatiotemporal variability (Qiu et al., 2021).

The development of artificial intelligence (AI), like machine learning (ML) and deep learning (DL), has surprisingly produced very high accuracy simulations for RE and water resources (Feng et al., 2020, 2022), opening up a plethora of opportunities to progress research in their nexus. The AI-based models are considered as the data-driven-based modeling approach. Unlike process-based models, AI-based models use data to obtain the relationships between variables of the system without including any form of physical processes within the system (Zhou, 2021, 2022a, 2022b). In addition, the AI-based models have a relatively higher computational efficiency and higher prediction accuracy that reduced the uncertainties presented in the processed-based models (Mentch & Hooker, 2016; Tiwari & Adamowski, 2015; Wani et al., 2017). However, AI-based models still need to be developed. For instance, as the AI-based models are data-driven-based, it requires sufficient training data or uneven class balance within the datasets to train and test the model to get accurate predictions. Thereby, the AI-based model is difficult to be applied in a field where there is a lack of complete input data. With this respect, many researchers have proposed some data augmentation techniques (Wen et al., 2021). As the energy, water, and environment-related data are highly accessible through global databases (Brockway et al., 2019; Sheffield et al., 2018), there is a high potential to apply AI-based models to the REWE nexus. More precisely, AI techniques can be adopted in modeling the interaction of resources in the REWE nexus.

Overall, this chapter aims to comprehensively and systematically review the recent applications of AI techniques to the REWE nexus. Following the introduction, the rest of this chapter is organized as follows: Section 12.2 presents and analyzes the common AI technologies/algorithms that are applied in REWE fields. Section 12.3 summarizes AI applications in the REWE nexus. Section 12.4 analyzes the application feasibility of AI techniques in the city-level REWE nexus. Then, the challenges and barriers to their implementations are identified in Section 12.5. Finally, Section 12.6 presents the future perspectives for the applications of AI to the nexus of REWE.

12.2 Common AI techniques for the REWE nexus

This section aims to present different AI techniques that have been applied within the framework of REWE. These AI techniques will be discussed in three types: (1) supervised learning (SL); (2) unsupervised learning (UL), and (3) reinforcement learning (RL). Here, two interlinked organizations are provided. The first organization follows the typical categories of AI approaches, and the second organization follows the application of different AI algorithms in the field of REWE. Fig. 12.1 presents the overview of general AI techniques that have been used within the framework of REWE.

12.2.1 Supervised learning

SL is an ML paradigm that has been widely used in various scientific fields (Verma et al., 2021), is used for the available data containing labeled examples. Namely, each data point consists of features and a corresponding label. The SL aims to learn a function $f:(x \rightarrow y)$ that maps the independent variables (inputs: x) and the dependent variables (outputs: y). The SL is used by applying ML algorithms on the "training data" by which the learned model will be obtained as the output. Then, this model will be tested on the new dataset (i.e., "test data" or "unseen data") for the purpose of predicting outputs or target variables for that data. The application of SL in the field of REWE mainly includes the algorithms of regression analysis (RA), artificial neural network (ANN), support vector machine (SVM), and decision tree (DT).

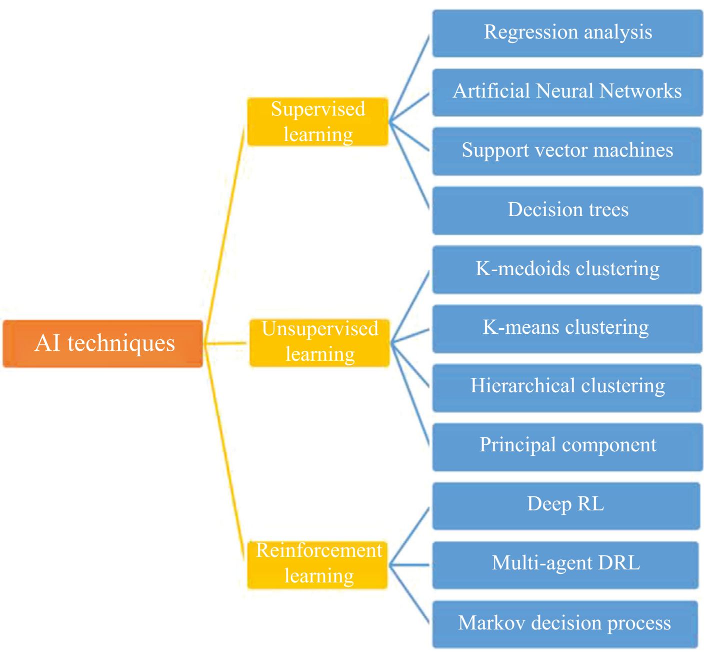

Figure 12.1 Overview of general artificial intelligence techniques that have been applied for analyzing renewable energy, water, and the environment.

12.2.1.1 Regression analysis

RA is a typical SL algorithm that is used for mapping the relationship between one or various independent variables (x) with one dependent variable (y). In the water-energy nexus studies, RA is employed for forecasting regional energy use and water demand (Cook et al., 2015; Wang et al., 2022). Amiri et al. (2015) used stepwise regression to select the most effective parameter for modeling and predicting energy consumption in commercial buildings. Villarín (2019) employed a multivariate linear regression model to study domestic water consumption at a fine spatial scale, and the obtained results provided suggestions for urban planning and management (Villarín, 2019).

RA accompanied by time series has been widely used for forecasting short-term water demand. For instance, Sebri (2016) forecasted urban water demand with a meta-analytical approach. Fumo and Rafe Biswas (2015) performed simple and multiple linear regression analysis accompanied by quadratic regression analysis on the data from a research house with different temporal resolutions, from hourly to daily (Fumo & Rafe Biswas, 2015).

12.2.1.2 Artificial neural networks

ANNs are also powerful SL algorithms that have been used for forecasting energy generation, consumption, water demand, and environment changes. ANNs can effectively learn from nonlinear data by using activation functions, like sigmoid, ReLU, and tanh. Fig. 12.2 shows a typical ANN architecture consisting of one input layer, one hidden layer, and one output layer.

For the aspect of energy generation and consumption, the first application of the ANNs was found by Kalogirou et al. (1998), who modeled the transient heat-up response of a steam generation system. Then, it has been widely used for predicting energy extraction (Kalogirou et al., 1999; Manohar et al., 2006). Bugała and Bednarek (2018) forecasted the electric energy from photovoltaic (PV) conversion by using ANN. It is notable that ANN has many advantages in forecasting variables. However, the ANN model depends on several initial parameters, like weights and biases (Kolen & Pollack, 1990). Hence, in order to improve the performance of ANN-based models, many studies developed hybrid models by integrating them with optimization algorithms. For instance, Bui et al. (2020) developed a hybrid model to forecast the energy consumption in buildings based on the combination of the electromagnetism-based firefly algorithm and ANN (Bui et al., 2020).

In terms of the water and environment aspect, ANN has proved to be useful in accurately estimating the hydrological variables (e.g., groundwater levels) compared to traditional hydrological/hydrodynamic models (Dash et al., 2010; Derbela & Nouiri, 2020). ANN models present nonlinear relationships among the hydrological variables that can be represented and reproduced. Jain and Kumar (2007) developed a hybrid ANN model to predict hydrologic time series by using monthly streamflow data. They indicated that the new hybrid approach can capture the

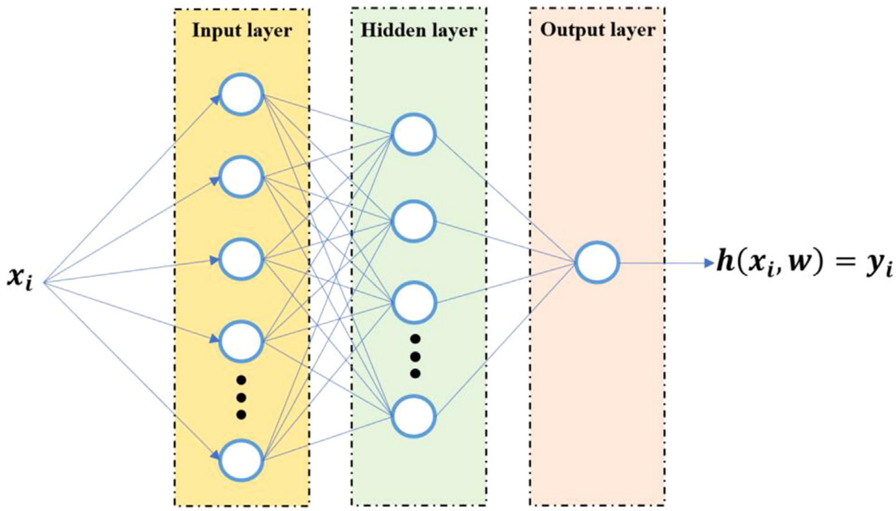

Figure 12.2 The general architecture of an artificial neural network model.
Source: Modified from Silva, C., Ribeiro, V., Coelho, P., Magalhães, V. & Neto, P. (2017). Job shop flow time prediction using neural networks. *Procedia Manufacturing*, 11, 1767–1773. https://doi.org/10.1016/j.promfg.2017.07.309. With permission from Elsevier, License Number: 5475910621502.

nonlinear nature of the complex time series and thus generate more accurate forecasts (Jain & Kumar, 2007).

12.2.1.3 Support vector machines

SVM is a powerful SL algorithm that has been successfully applied for classification and regression. SVM uses three different kernels, namely, linear kernel, polynomial kernel, and radial basis function kernel (Hossain et al., 2012). Zendehboudi et al. (2018) comprehensively reviewed the SVM models for forecasting solar and wind energy resources. They indicated that the SVM is more effective with the experimental data samples, and the hybrid SVM with evolutionary algorithms has higher accuracy than other models for predicting both solar and wind energy for various locations (Zendehboudi et al., 2018). Furthermore, SVM has been largely applied to forecast short-term wind power (Liu et al., 2017; Zhang et al., 2012), water levels of lakes or dams (Hipni et al., 2013; Khan & Coulibaly, 2006), and air and water quality prediction (Yunrong & Liangzhong, 2009).

12.2.1.4 Decision trees

DTs are the nonparametric SL algorithms used for classification and regression. The DT algorithms are easy to understand, interpret, and visualize, while their high variance may lead to an overfitting problem. DT has been used for predicting energy use by many researchers (Mikučioniene et al., 2014; Yu et al., 2010). DT algorithms can generate rules or logic statements that are easy to be interpreted. Saghebian et al. (2014) proposed a DT-based approach to predict groundwater quality. The results showed the suitability of the DT-based classification approach for the used datasets (Saghebian et al., 2014). Lu and Ma (2020) proposed two hybrid DT-based models to predict the water quality and applied the models to the most polluted river of Tualatin River in Oregon, United States (Lu & Ma, 2020).

12.2.2 Unsupervised learning

With the increase of a large number of unlabeled data, UL algorithms provided more opportunities for advancing research associated with automatically discovering useful patterns in such data. Unlike SL algorithms, UL algorithms are based on discovering hidden structures from unlabeled data. Commonly used UL algorithms in the REWE field comprise of K-means clustering (Aytaç, 2020; Manohar et al., 2006), hierarchical clustering, and principal component analysis (Alloghani et al., 2019). Fig. 12.1 presents several typical unsupervised algorithms adopted for the REWE fields. Noiva et al. (2016) applied a hierarchical cluster analysis to investigate the water supply and demand for 142 cities globally. Helmbrecht et al. (2017) used hierarchical clustering in conjunction with business rule techniques for monitoring water supply systems and management of water resources to increase energy efficiency. Indeed, these UL algorithms have shown good performances in energy use disaggregation, but they have some limitations in terms of handling appliances in multiple operating modes simultaneously. Thereby, some researchers proposed a novel sparse-based optimization approach (Piga et al., 2016) to address this limitation. He et al. (2020) adopted unsupervised deep learning for extracting energy consumption features, and the results show that the energy prediction performance was improved by the proposed method (He et al., 2020).

In terms of the UL algorithms used for water resources, several studies combined different ML techniques (e.g., hidden Markov models, dynamic time warping, and ANN) for the classification of water consumption (Nguyen et al., 2013). Principal component analysis (PCA) is another UL-based feature transformation technique that is adopted to explore variations of inputs or independent variables. In recent years, PCA and the PCA mixed-precision neural networks have been widely applied in the energy and water sectors (Chakraborty et al., 2020; McManamay, 2014).

12.2.3 Reinforcement learning

RL is one of the three basic ML paradigms alongside SL and UL (Sutton & Barto, 2018), which is based on learning the behavior of agents by obtaining feedback from the environment. In terms of SL, the labeled training datasets are learned based on limited inputs that may not be able to consider various situations that are unseen in the future. Andrew (1999) indicated that the SL might not be an appropriate approach for addressing interactive problems, and RL tends to perform better because it constantly interacts with the environment in getting responses for its actions. In terms of UL, it also has some limitations in detecting structural patterns within the examples in the data, but RL can maximize the reward signals regarding interactions of the agent with its environment. The typical RL algorithms include the Markov decision process (MDP), advanced deep RL, and multi-agent DRL (Cao et al., 2020).

Misra et al. (2013) presented an MDP-based scheduling mechanism for managing residential energy in a smart grid. Li and Sun (2013) developed an analytical model based on MDP to analyze the complex interactions between the adopted energy control decisions and system state evolutions. Huong et al. (2018) proposed a generic irrigation model based on MDP for energy- and water-efficient farming. To support the sustainable development of the river ecological environment, Chen et al. (2023) developed a multi-objective coupled water and sediment regulation model based on a reinforcement Q-learning algorithm to minimize sedimentation and inundation loss, and maximize ecological value in the lower Yellow River basin. Overall, the application of RL in the water and energy fields enlightened the possibility of further applications of developing AI-based models in addressing optimization and forecast problems.

12.3 Literature review on the AI application in the REWE nexus

Due to their ability to solve nonlinear and complex data structures, AI techniques have been extensively used to solve issues related to individual elements of REWE nexus (i.e., RE (Zhang et al., 2022), water (Danish, 2022), and the environment (Nti et al., 2022)). For instance, Magazzino et al. (2021) studied an ML approach to the causal relationship among solar and wind energy production, coal consumption, economic growth, and CO_2 emissions in the United States, China, and India. Also, Chen et al. (2021) presented an AI-based useful evaluation model for predicting RE technologies and energy efficiency impact on the economy and reported 97.32% energy efficiency and increased use of RE using the model (Chen et al., 2021). Furthermore, Zhang et al. (2022) comprehensively reviewed AI applications in solving issues related to RE. A review of AI applications in water resources engineering can be found in Danish (2022). Nti et al. (2022) summarized AI applications in environmental sustainability issues such as biodiversity, energy, transportation, and water management (Nti et al., 2022). However, few studies can be found in the literature on the application of AI in the REWE nexus.

AI can be applied in RE-driven desalination systems for expert decision-making (e.g., site selection, desalination technology selection), operating parameter optimization (e.g., energy parameters, structure or size parameters, feed parameters, and surrounding parameters), parameter prediction, and control by sequence. He et al. (2022) reviewed AI applications in seawater desalination systems based on RE. They concluded that ANN and genetic algorithm (GA) are the most utilized intelligent algorithms in these systems. Because of their features, ANN is preferred in the prediction process of RE-driven desalination systems, and GA is useful in the optimization process (He et al., 2022).

High penetration levels of RE sources such as wind energy and PV generation can create some challenges in the power grids (e.g., the duck curve and unreliability) because of their intermittent nature. Electric water heaters (EWHs) can be considered as a candidate for demand response because of their energy storage capability. Mabina et al. (2021) reviewed ML models for energy optimization and scheduling of EWHs in smart grids and smart building environments. Based on the review of the existing studies, they concluded that the proposed ML models in the literature do not present a solution that fully provides ancillary services under high penetration of RE sources, and this field can be a trending future research topic (Mabina et al., 2021).

Surface evaporation from reservoirs wastes water, and shading the surface of pond can prevent evaporation. Soltani et al. (2022) used an AI technique to study the effect of a floating PV system on water loss through surface evaporation in the Yazd wastewater pond near the city of Yazd, Iran. The evaporation reduction change due to the floating PV system from 272.7 ha in January 2021 to 413.9 ha in November 2025 was reported. Overall, up to 70% evaporation decrease from the pond was predicted (Soltani et al., 2022).

12.4 Application feasibility of AI for city-level REWE nexus

Interactions among RE, water, and the environment have considerable variations across regions due to factors of climate, population density, and economic development level, among others (Bauer et al., 2014). Moreover, the nexus of REWE is inherently impacting urban development, and thereby, it is necessary to get useful insights into the function of REWE at the city level. With the rapid development of AI techniques, it is feasible to develop AI-based models to predict the REWE elements (Zaidi et al., 2018).

Predicting variables in advance by using historical data is a significant task in analyzing the behavior and trends of variables related to the REWE. For example, Worland et al. (2018) compared the performances of eight ML-based models and four baseline models to predict the annual minimum 7-day mean streamflow at 224 unregulated sites in South Carolina, Georgia, and Alabama, United States. The results showed that the ML-based models have higher accuracy compared to the baseline models. Furthermore, concerning the datasets used for modeling, it sometimes contains missing data or unobserved variables. There is an increasing interest in using AI-based models for modeling these variables. For instance, Thanh et al. (2022) employed six ML models, that is, random forest (RF), Gaussian process regression, support vector regression, DT, least squares support vector machine, and multivariate adaptive regression spline (MARS) models, to reconstruct the missing daily-averaged discharge in a mega-delta from 1980 to 2015. The results indicated that the ML model outperformed the rating curve (RC) model, and that the MARS model and RF model were the most reliable algorithms, although the MARS model performed slightly better than the RF model. Compared to the RC model, the MARS model and RF model achieved a 135% and 141% reduction in root mean square error and a 194% and 179% reduction in mean absolute error, respectively, by using a whole year of available data (Thanh et al., 2022).

Nakhaei et al. (2022) used micro-hydro power (MHP) in the water distribution network (WDN) for energy recovery to recover wasted energy in the infrastructure, as shown in Fig. 12.3. This study was the first to design an AI-based framework for WDN energy harvesting assessment. After using the Environmental Protection Agency Network Evaluation Tool (EPANET) software to develop the modeling of WDN in Mashhad, Iran, this study improved the model prediction capability by applying the design of experiments methods including Taguchi and response surface methodology (RSM) followed by ANN techniques. Results presented from this investigation indicated that the combination of Taguchi and RSM methods can successfully optimize the energy recovery potential considering the improved hydraulic parameters of the WDN. By using RSM and Taguchi, high potential capacity for MHP placement was detected and analyzed based on high-performance operational decision-making methods. Based on AI calculations, energy harvesting and hydraulic response can be estimated with a correlation coefficient of more than 99%. The results showed that the MHP collected more than 400 kW of energy during the operation time considering the hydraulic parameters in this study (Nakhaei et al., 2022).

Tariq et al. (2021) proposed an AI-assisted techno-economic optimization scenario of hybrid energy systems for water management in isolated communities, as shown in Fig. 12.4. This study first used commercial software (hybrid optimization of multiple energy sources) and a spreadsheet algorithm to scale various hybrid energy systems and conducted a multi-objective optimization of the system using non-dominating sorting genetic algorithm II. The multi-objective optimization also involved environmental (CO_2 emissions) and water cost indices. A multi-criteria decision tool trumpet solution using the technique for order preference by similarity to an ideal solution is applied to the Pareto front to obtain the final optimization results. The analysis is further explored in depth by generating numerical twins (alternative models or metamodels) of hybrid RE systems data using AI techniques. In addition, calculus and statistical sensitivity analysis assisted in identifying important variables for the design process. The study showed that best-case scenarios included PV systems, diesel generators, and Li-ion battery storage technologies with capacities of $\sim$17 kW, $\sim$5 kW, and 44−48 kWh, corresponding to net present costs of $70,000 (USD) to $79,000 and electricity costs of $0.205 to $0.229/kWh, respectively. The results obtained from the multi-objective optimization showed that the cost of electricity and the net present cost could be further reduced by 0.86% and 0.73%, respectively, compared to the single-objective optimization scenario, with only a 0.4% reduction in the renewable component. The findings can provide a science-based explanation for national energy policymakers (Tariq et al., 2021).

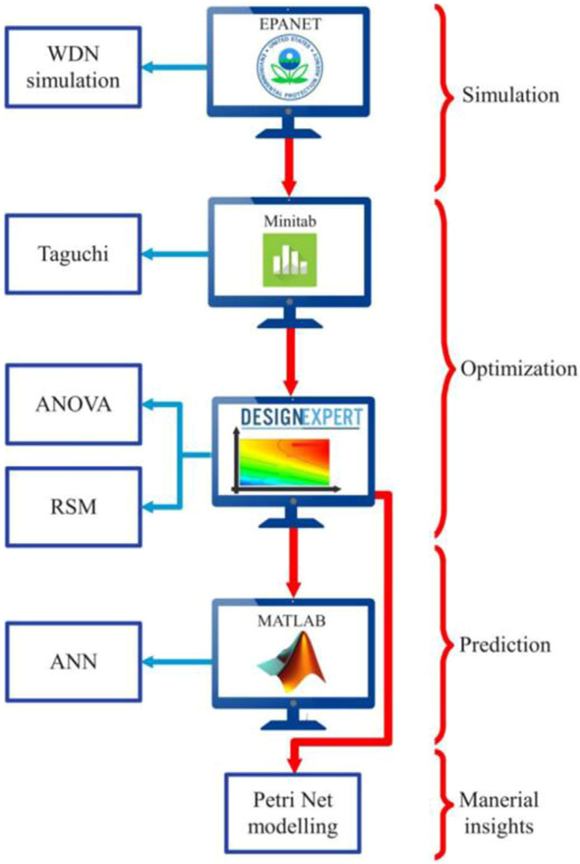

Figure 12.3 Research roadmap for technical performance assessment of water distribution networks based on the concept of water–energy nexus.
Source: From Nakhaei, M., Akrami, M., Gheibi, M., Daniel Urbina Coronado, P., Hajiaghaei-Keshteli, M. & Mahlknecht, J. (2022). A novel framework for technical performance evaluation of water distribution networks based on the water-energy nexus concept. *Energy Conversion and Management*, 273, 116422. https://doi.org/10.1016/j.enconman.2022.116422. Reproduced with permission from Elsevier, License Number: 5475910809386.

In practice, for investigating the REWE fields, it is difficult to use a single model for constructing relationships among variables for various resource systems within the nexus of REWE. With this respect, it is important to develop the model by integrating process-based models and data-driven-based models (Feng et al., 2022; Wang et al., 2019). For instance, Lin et al. (2021) proposed a hybrid model, namely, the DIFF (first-order difference)-FFNN (feedforward neural network)-LSTM (long short-term memory network), to predict hourly streamflow. This hybrid model was applied to the Andun Basin, China. The results showed that the

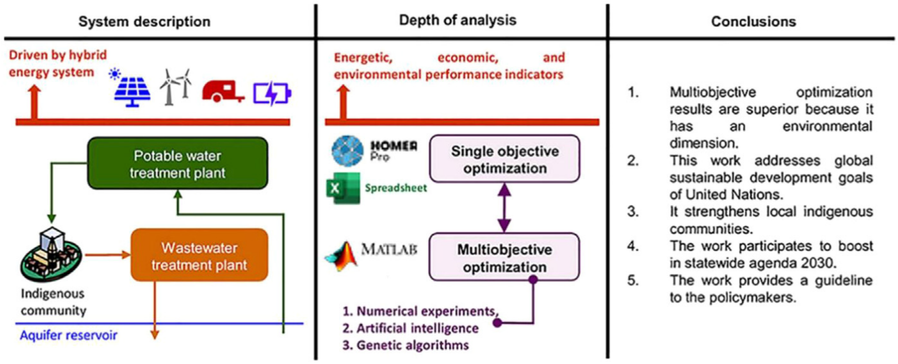

Figure 12.4 Research framework of AI-assisted techno-economic optimization scenario of hybrid energy systems for water management.
Source: From Tariq, R., Cetina-Quiñones, A. J., Cardoso-Fernández, V., Daniela-Abigail, H. L., Soberanis, M. A. E., Bassam, A. & De Lille, M. V. (2021). Artificial intelligence assisted technoeconomic optimization scenarios of hybrid energy systems for water management of an isolated community. *Sustainable Energy Technologies and Assessments*, *48*, 101561. https://doi.org/10.1016/j.seta.2021.101561. Reproduced with permission from Elsevier, License Number: 5475911137730.

hybrid model has good performance in predicting hourly streamflow for all the flood events in the testing period. For predicting energy consumption, Jogunola et al. (2022) proposed a hybrid deep learning framework in which the model is structured comprising a convolutional neural network (CNN), an autoencoder with bidirectional LSTM. The results showed that this hybrid model can accurately predict the energy consumption of different types of buildings (e.g., commercial and domestic) across different countries. They suggested extending the proposed framework for price estimation in an energy market, while evaluating the impact of RE sources (e.g., solar, wind) integration on the energy demand and price estimation (Jogunola et al., 2022). Overall, integrating process-based models and data-driven-based models brings new opportunities for predicting the nexus of REWE.

DL, as one part of ML methods, has been applied to the field of REWE at the city level (Sit et al., 2020; Wang et al., 2019). The typical DL algorithms include CNNs, LSTMs, recurrent neural networks, generative adversarial networks, radial basis function networks, multilayer perceptrons, and self-organizing maps. CNNs have been applied for image segmentation (Mosaffa et al., 2022) and mapping (Panahi et al., 2020). LSTMs have been applied for predicting time series data (Widiasari et al., 2018). Some studies also combined CNN with LSTM. For example, Deng et al. (2022) proposed a daily runoff forecasting model on the basis of the combination of CNN and LSTM models. They applied this model in the Feilaixia catchment and investigated the influence of various input parameters. The results showed that the CNN–LSTM model has better performance than that of the LSTM model in runoff forecasting. Besides integrating different DL models, some researchers also developed some hybrid models based on the combination of the

DL model and physically based process model. For instance, Feng et al. (2022) developed a hybrid model by integrating LSTM and a process-based hydrological model. The hybrid model was applied to 671 basins across the United States and showed a good performance in the prediction of hydrological variables (Feng et al., 2022). Nevertheless, the development of DL algorithms brings larger feasibility for analyzing REWE fields.

12.5 Challenges and barriers for AI application to the REWE nexus

In recent years, the rapid advancement of information technology with AI as the core has provided new opportunities for disruptive development in the field of REWE from traditional empirical and qualitative decision-based strategies to precise and quantitative intelligent decision-making (Elyasichamazkoti & Khajehpoor, 2021; McMillan & Varga, 2022). Meanwhile, it also creates the possibility for future-oriented reconfiguration of healthy, sustainable, highly resilient, and intelligent systems in the nexus of REWE. The rapid advancement of AI technology has injected new vitality into the development and application of technologies from micro- to meso- and macro-scales for risk prevention and control, safety and security, and optimal management of systems in the nexus of REWE, thereby bringing a series of positive effects to accelerate the process of achieving the carbon neutrality target. Nevertheless, many new challenges remain to be faced in achieving this objective. Throughout the scientific exploration and practice described in the previous sections, there are still several key issues that need to be addressed in the future applications of AI techniques/technologies in the REWE nexus:

1. Integration with existing systems in the nexus of REWE: One of the challenges in applying AI in REWE nexus is the integration of AI solutions with existing systems and their processes. To be effective, AI solutions require seamless integration with the systems and processes that they are intended to enhance. However, this may be a challenge as it requires a deep understanding of how these systems work and how they can be augmented with AI. In practice, AI needs to be compatible with the hardware, software, and protocols used in existing REWE systems, which may be difficult because it commonly requires specialized hardware or software that is not compatible with existing systems (Kelly et al., 2023).
2. Data availability and quality: To effectively train and evaluate AI models, a substantial amount of high-quality data is required (Torregrossa et al., 2016). However, the data in the REWE nexus are often scarce, unstructured, and/or of poor quality, which may make it difficult to develop accurate and reliable AI models. The main factors affecting the availability and quality of data in the REWE nexus include: (1) Data in the REWE nexus may be collected from a variety of sources, including governmental agencies, research institutions, and industry. Accessing these data sources may be limited or require special permission, which may hinder the development of AI models. (2) There can be different formats and structures of data from different sources, which may make the integration and analysis of data related to the REWE nexus very problematic. (3) It is critical for the

accuracy and completeness of data to develop accurate and reliable AI models, and missing, incomplete, or incorrect data can lead to deviations or deficiencies in AI models (Edwards et al., 2017).

3. Interdisciplinary professional knowledge: the study of the REWE nexus involves complex interactions of physical, chemical, biological, and social systems. Therefore, the development of AI solutions in this field requires a multidisciplinary team with expertise in multiple disciplines, including engineering, environmental science, computer science, and social science (Langer et al., 2021; Skowronek et al., 2022), as follows: (1) Designing and implementing AI solutions that can address the challenges in the REWE nexus require specialized engineering knowledge, which may include knowledge in electrical engineering, mechanical engineering, chemical engineering, and materials science. (2) This specialized knowledge is required to understand the impacts on the natural environment, as well as to identify and address potential environmental risks, which may include expertise in areas such as hydrology, meteorology, and ecology. (3) Designing and implementing AI algorithms and systems require computer science-specialized knowledge, which may include specialized knowledge in ML, data science, and software engineering. (4) This professional knowledge is required to understand the social and cultural implications of AI solutions in the context of REWE, which may include professional knowledge in areas such as psychology, sociology, and economics.
4. Regulatory and policy issues: In the REWE nexus, AI deployment tends to be subject to regulatory and policy constraints, which may vary depending on the location and nature of the AI applications, and can be complex and time-consuming. Navigating these constraints may be challenging and requires a thorough understanding of the relevant regulations. The collection and usage of data in a REWE nexus may involve sensitive information, such as personal or proprietary data. Ensuring the privacy and security of these data is critical to the responsible usage of AI in this field. This may involve compliance with laws and regulations related to data privacy and security, such as the EU's General Data Protection Regulation (GDPR) (Tamburri, 2020). AI solutions in the REWE nexus may be governed by environmental regulations, such as those related to air and water quality, waste management, and resource protection. In general, it is important to ensure that AI is developed and used in compliance with relevant laws and regulations, considering ethical guidelines and government policies (Belli et al., 2023; Qerimi & Sergi, 2022). This will contribute to ensuring that AI is used in a responsible and beneficial manner in the REWE nexus.
5. Cost of solutions: The cost of developing and deploying AI solutions is probably a major barrier to their application in the REWE nexus. First, AI solutions require large amounts of high-quality data for training and evaluation, and acquiring and preprocessing this data can be time-consuming and expensive. Then, integrating AI solutions with existing systems and processes can be challenging and time-consuming, which can increase the cost of deployment. In addition, AI solutions require continual maintenance and updates to remain accurate and effective, which may involve ongoing costs for data collection, training, and evaluation. In the context of the REWE nexus, decreasing the cost of an AI solution may involve finding approaches to minimize data collection, hardware and software, expertise and integration with existing systems, and optimizing the continued maintenance of AI solutions.
6. Ethical considerations: AI solutions in this area have the potential to create significant impacts on humans and the environment, and therefore it is important to consider the ethical implications of these impacts and to develop AI solutions that are equitable, transparent, and accountable (John-Mathews, 2022; Mark & Anya, 2019; Mezgár & Váncza,

2022). AI algorithms may be biased if the available data used to train them are biased, which can lead to unfair and inequitable outcomes, such as the exclusion of certain groups or the perpetuation of existing inequalities (Gevaert et al., 2021). It is important to ensure that AI solutions are trained on diverse and representative data to minimize bias, which may involve considering the distribution of benefits and harms and ensuring that the demands and interests of all stakeholders are considered.

7. Cultural and social acceptance: Widespread adoption of AI in the REWE nexus may be limited by cultural and social factors, and these barriers can affect the development and deployment of AI applications. The public may have misconceptions or misperceptions about AI, which may lead to distrust or resistance to its use. Some public may not have sufficient understanding of how AI works, which may make them cautious about its use. There may be concerns that the adoption of AI will lead to job loss or other negative effects on employment. To address these cultural and social acceptance barriers, it is important to communicate transparently and openly about the development and usage of AI and to address concerns and misconceptions about this technology (Pelau et al., 2021; Yuan et al., 2022). It is also important to ensure that AI is developed and used responsibly, ethically, and for the benefit of society.

12.6 Conclusions and future perspectives

AI has been rapidly developing in recent years, and it is already used in the REWE fields and its related industries (Doshi & Varghese, 2022; Leal Filho et al., 2022; Ouafiq et al., 2022). This chapter presented and analyzed the AI technologies that are applicable to RE, water, and the environment fields, respectively, and categorized and integrated them. Also, the chapter summarized the AI application in the REWE nexus. Furthermore, the chapter analyzed the application feasibility of AI for establishing city-level REWE nexus studies from the different application scenarios. In addition, the chapter identified some promoting challenges and barriers to the application of AI technologies to the REWE nexus.

To enable AI to better contribute to the REWE nexus, some targeted development recommendations and future research perspectives are presented below:

1. AI can be used to optimize the operation of RE systems, such as solar panels and wind turbines. This may involve the application of ML algorithms to predict energy production and optimize energy storage systems, as well as the usage of sensors and other monitoring technologies to track the performance of RE systems in real-time (Al-Othman et al., 2022; Liu, Sun, et al., 2022; Zhou, 2022a, 2022b). Within the REWE nexus, AI can be used to predict the amount of energy that will be produced by an RE system, which can contribute to optimizing the usage of the energy generated, ensuring that the energy will be used when it is most needed or when it is most efficient.
2. AI can be used to monitor and optimize water use in agriculture, industry, and other sectors. This may involve using ML algorithms to predict water demand and optimize irrigation systems, as well as using sensors and other monitoring technologies to track water usage in real-time. AI can be used to predict water demand and optimize irrigation systems to minimize water waste, which may involve using data on factors such as weather

conditions, soil moisture, and plant growth to predict the amount of water required at different times and adjust irrigation systems accordingly.

3. AI can be used to design and optimize sustainable infrastructure, such as smart cities, that are designed to be more energy- and water-efficient and minimize their environmental impacts. This may involve the usage of ML algorithms to analyze data from sensors and other monitoring systems to identify patterns and trends that can be used to optimize the design and operation of infrastructure. In the REWE nexus, there are several ways in which AI can be used to design and optimize sustainable infrastructure, for example, by analyzing performance data from existing infrastructure and using this information to inform the design of new infrastructure that is more energy- and water-efficient.
4. AI can be used to optimize the usage of natural resources, such as predicting and managing demand for resources like water and energy, and to assist in identifying and prioritizing conservation and restoration efforts, which may involve using ML algorithms to analyze data from sensors and other monitoring systems to identify patterns and trends that can be used to optimize resource usage. Some methods for optimizing natural resource use are available for AI applications related to the REWE nexus.

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