Information Systems Engineering and Management 6

Yousef Farhaoui *Editor*

Artificial Intelligence, Big Data, IOT and Block Chain in Healthcare: From Concepts to Applications

Volume 2

Springer

Information Systems Engineering and Management 6

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ISSN 3004-958X ISSN 3004-9598 (electronic)
Information Systems Engineering and Management
ISBN 978-3-031-65017-8 ISBN 978-3-031-65018-5 (eBook)
https://doi.org/10.1007/978-3-031-65018-5

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

"Artificial Intelligence, Big Data, IoT & Blockchain: From Concepts to Applications" is a comprehensive exploration of the transformative potential of cutting-edge technologies in shaping various aspects of our lives. This expansive book delves into the core concepts and practical applications of artificial intelligence (AI), big data, Internet of things (IoT), and blockchain, elucidating their profound impact on industries, societies, and economies worldwide.

At its essence, AI represents the pinnacle of human ingenuity, enabling machines to simulate human-like intelligence and perform tasks that traditionally require human cognition. Through advanced algorithms and data-driven insights, AI holds the promise of revolutionizing industries ranging from healthcare and finance to transportation and entertainment.

Big data, on the other hand, refers to the vast volumes of structured and unstructured data generated in our digital age. Harnessing the power of big data analytics allows organizations to extract valuable insights, identify trends, and make informed decisions at an unprecedented scale. From personalized marketing strategies to predictive maintenance in manufacturing, the applications of big data are virtually limitless.

The Internet of things (IoT) further extends the reach of interconnected devices, enabling seamless communication and data exchange between physical objects and digital systems. By embedding sensors and connectivity into everyday objects, IoT facilitates automation, optimization, and enhanced user experiences across diverse domains, including smart homes, healthcare monitoring, and industrial automation.

Meanwhile, blockchain technology introduces a paradigm shift in trust and decentralization, offering transparent and immutable ledgers for recording transactions securely. Originally conceived as the underlying technology for cryptocurrencies like Bitcoin, blockchain has evolved to disrupt various industries, from supply chain management and voting systems to intellectual property rights and decentralized finance (DeFi).

Throughout this book, readers will embark on a journey that traverses the theoretical foundations, practical implementations, and future prospects of these transformative technologies. Through insightful discussions, real-world case studies, and expert perspectives, readers will gain a comprehensive understanding of AI, big data, IoT, and blockchain and their role in driving innovation, fostering economic growth, and addressing societal challenges in the digital age.

Whether you're a seasoned professional seeking to deepen your knowledge or a curious enthusiast eager to explore the frontiers of technology, "Artificial Intelligence, Big Data, IoT & Blockchain: From Concepts to Applications" serves as an indispensable guide to navigating the dynamic landscape of modern innovation. Dive into this captivating exploration and discover the limitless possibilities that await in the realms of AI, big data, IoT, and blockchain.

Contents

Iterative Method of Newton-Raphson for Systems with Two Equations

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Abstract. In numerical analysis, the Newton-Raphson method for systems of equations extends the idea of the Newton-Raphson method for single-variable equations to systems of equations. In the case of a system of two equations, it helps to find the simultaneous solutions to both equations. The Newton-Raphson method for systems with two equations can be particularly useful in optimization problems, finding the intersection of curves, solving nonlinear systems of equations, and many other applications where finding the roots of a system of equations is required. This paper describes in a detailed way the iterative method of Newton-Raphson for systems with two equations. Next, two algorithmic implementations of the iterative method of Newton-Raphson for systems with two equations are developed in Python and Java Programming language, with special focus on the use of computing in the scientific field of mathematics.

Keywords: Computer science · Mathematics · Algorithms

1 Introduction

The Newton-Raphson method for systems of equations extends the idea of the Newton-Raphson method for single-variable equations to systems of equations. In the case of a system of two equations, it helps to find the simultaneous solutions to both equations. The Newton-Raphson method for systems with two equations can be particularly useful in optimization problems, finding the intersection of curves, solving nonlinear systems of equations, and many other applications [1–15]. However, as with any numerical method, it is important to exercise caution and conduct thorough convergence analysis to ensure reliable results [1, 2]. The Newton-Raphson method for systems of equations is a powerful iterative technique for finding solutions to simultaneous equations. It iteratively updates an initial guess for the solution until it converges to a point where both equations are approximately zero [12–16]. However, caution must be exercised regarding robustness and convergence, especially in the presence of multiple solutions or singularities [17–36].

2 Mathematical Background

The Newton-Raphson method can be extended to solve systems of equations. For a system with two equations: f(x,y) = 0 and g(x,y) = 0 we would use the following iterative scheme:

Y. Farhaoui (Ed.): BDBI 2024, ISEM 6, pp. 1–8, 2024.
https://doi.org/10.1007/978-3-031-65018-5_1

1. Start with an initial guess for the solution (x_0, y_0).
2. At each iteration k, compute the Jacobian matrix:
   $$J(x_k, y_k) = \begin{pmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \\ \frac{\partial g}{\partial x} & \frac{\partial g}{\partial x} \end{pmatrix}$$
3. Evaluate the function values $f(x_k, y_k)$ and $g(x_k, y_k)$.
4. Solve the linear system:
   $$J(x_k, y_k) = \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} = \begin{pmatrix} -f(xk, yk) \\ -g(xk, yk) \end{pmatrix}$$ to find the updates Δx and Δy.
5. Update the solution:
   $x_k = x_k + \Delta x$
   $y_{k+1} = y_k + \Delta y$
6. Repeat steps 2–5 until convergence, usually defined by the magnitude of the change in the solution being below a certain threshold.

This process is repeated until the desired level of accuracy is accomplished. However, it is worth noting that Newton's method may not always converge or may converge to a local minimum depending on the initial guess and the properties of the functions involved. Therefore, it is often wise to use a hybrid method that combines Newton's method with other techniques to ensure robustness.

Convergence and Robustness: Newton's method can converge quickly to a solution when it exists, and the initial guess is close enough to it. However, it may fail to converge or converge to a wrong solution if the initial guess is far from the actual solution, or if the system of equations has complex behavior, such as multiple solutions or singularities. To address this, it is common to incorporate safeguards like maximum iteration limits or hybrid methods that combine Newton's method with other techniques for increased robustness. Newton-Raphson method for systems of equations is a powerful iterative technique for finding solutions to simultaneous equations, provided appropriate precautions are taken for robustness and convergence.

3 Algorithmic Implementation in Python Programming Language

Below is a Python implementation of the Newton-Raphson method for solving a system of two equations. This implementation uses NumPy for numerical computations.

```
import numpy as np

def newton_raphson_system(f, g, J, initial_guess, tol=1e-6,
max_iter=100):

    """

    Newton-Raphson method for solving a system of two equations:

    f(x, y) = 0

    g(x, y) = 0
```

```
    Parameters:
        f: Function representing the first equation.
        g: Function representing the second equation.
      J: Function representing the Jacobian matrix of the system.
        initial_guess: Initial guess for the solution (x, y).
        tol: Tolerance for convergence.
        max_iter: Maximum number of iterations.
    Returns:
        sol: Solution to the system of equations (x, y).
        num_iter: Number of iterations performed.
    """
    x, y = initial_guess
    for i in range(max_iter):
        # Evaluate functions and Jacobian at current guess
        fx, gy = f(x, y), g(x, y)
        jac = J(x, y)
        # Solve linear system J * [delta_x, delta_y] = [-f, -g]
for delta_x and delta_y
        delta = np.linalg.solve(jac, np.array([-fx, -gy]))
        # Update guess
        x += delta[0]
        y += delta[1]
        # Check for convergence
        if np.linalg.norm(delta) < tol:
            return (x, y), i+1  # Solution found
    return (x, y), max_iter
# Reached maximum iterations without convergence
# Example system of equations
def f(x, y):
    return x**2 + y**2 - 1  # Circle equation
def g(x, y):
    return x - y  # Diagonal line
# Jacobian matrix of the system
def J(x, y):
    return np.array([[2*x, 2*y], [1, -1]])
```

```
# Initial guess
initial_guess = (1.0, 0.5)
# Solve the system
sol, num_iter = newton_raphson_system(f, g, J, initial_guess)
print("Solution:", sol)
print("Number of iterations:", num_iter)
```

This code defines the ‘newton_raphson_system’ function, which takes the functions representing the equations (‘f’ and ‘g’), the function representing the Jacobian matrix (‘J’), the initial guess for the solution, and optional parameters for tolerance and maximum iterations. It iteratively applies the Newton-Raphson method until convergence or until the maximum number of iterations is reached. In this example, the system consists of a circle equation and a diagonal line, and the initial guess is provided as (‘1.0, 0.5)’. The Jacobian matrix is computed analytically. Finally, the solution and the number of iterations performed are printed.

4 Algorithmic Implementation in Java Programming Language

Below there is an implementation of the Newton-Raphson method for solving a system of two equations in Java programming language:

```
import org.apache.commons.math3.analysis.MultivariateFunction;
import
org.apache.commons.math3.analysis.differentiation.DerivativeStru
cture;
import
org.apache.commons.math3.analysis.solvers.NewtonRaphsonSolver;


public class NewtonRaphsonSystemSolver {


    public static void main(String[] args) {
        // Example system of equations:
        // f(x, y) = x^2 + y^2 - 1 = 0 (Circle equation)
        // g(x, y) = x - y = 0 (Diagonal line)


        // Define the functions
   MultivariateFunction[] functions = new MultivariateFunction[]{
          point -> point[0] * point[0] + point[1] * point[1] - 1,
            point -> point[0] - point[1]
        };
        // Define the Jacobian matrix
MultivariateFunction[][] jacobian = new MultivariateFunction[][]{
            {point -> 2 * point[0], point -> 2 * point[1]},
```

```
                {point -> 1.0, point -> -1.0}
            };

            // Initial guess
            double[] initialGuess = {1.0, 0.5};

            // Create Newton-Raphson solver
            NewtonRaphsonSolver solver = new NewtonRaphsonSolver();

            // Solve the system
            double[]   solution   =   solver.solve(100,   functions,
jacobian, initialGuess);

            // Print the solution
            System.out.println("Solution:");
            for (int i = 0; i < solution.length; i++) {
                System.out.println("x[" + i + "] = " + solution[i]);
            }
        }
    }
```

This code uses the Apache Commons Math library, which provides implementations for numerical algorithms. In this example, we use 'NewtonRaphsonSolver' class to solve the system of equations. We define the system of equations as an array of functions ('functions') and the Jacobian matrix as a 2D array of functions ('jacobian'). Then, we provide an initial guess for the solution and call the 'solve' method of the 'NewtonRaphsonSolver' to find the solution.

5 Conclusions

The Newton Raphson method is indeed versatile and finds applications in various fields due to its ability to efficiently find solutions to systems of equations. Specifically:

1. **Optimization Problems**: Many optimization problems involve finding the minimum or maximum of a function, which often requires solving systems of equations. The Newton-Raphson method can be employed to iteratively find the critical points of the objective function, aiding in optimization processes.
2. **Curve Intersection**: In geometry and graphics, curves often intersect at points that satisfy a system of equations. The Newton-Raphson method can be used to find these intersection points accurately, enabling tasks like curve fitting and geometric modeling.
3. **Nonlinear Systems of Equations**: Many real-world problems involve nonlinear relationships between variables, leading to systems of nonlinear equations. The Newton-Raphson method provides an effective approach to solving such systems, enabling analysis and modeling in diverse fields such as physics, economics, and biology.

4. **Dynamic Systems**: Systems of ordinary differential equations frequently arise in modeling dynamic systems, such as mechanical systems, electrical circuits, and chemical reactions. The Newton-Raphson method can be adapted to solve the resulting systems of equations, facilitating the analysis and simulation of dynamic behaviors.
5. **Error Analysis and Convergence**: Understanding the convergence properties of the Newton-Raphson method is crucial for its successful application. Careful consideration of the initial guess, system properties, and numerical stability is essential to ensure convergence and accuracy in practical scenarios.

Overall, the Newton-Raphson method provides a powerful tool for solving systems of equations in various contexts, contributing to problem-solving and decision-making processes across numerous disciplines. However, as with any numerical method, it is important to exercise caution and conduct thorough convergence analysis to ensure reliable results.

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Harnessing Reinforcement Learning for Enhanced Solar Radiation Prediction: State-of-the-Art and Future Directions

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Abstract. Solar radiation prediction is critical for optimizing the performance of solar energy systems, yet traditional methods often need help to capture the complexity of this phenomenon. In recent years, reinforcement learning (RL) has emerged as a promising approach to address this challenge by enabling autonomous learning and decision-making in dynamic environments. This review paper presents a comprehensive overview of the state-of-the-art harnessing of RL techniques for enhancing solar radiation prediction. Our analysis is based on a systematic Scopus advanced search, which yielded 25 relevant documents published between 2018 and 2024. We categorize existing literature based on modeling strategies, input data sources, and evaluation methodologies, providing insights into key findings and approaches. We discuss the choice of RL algorithms, input feature selection, reward design, and model evaluation metrics. Additionally, we identify challenges such as data scarcity, interpretability issues, and generalization concerns and discuss potential solutions. Furthermore, we outline future research directions and emerging trends in the field, including transfer learning, domain adaptation, and multi-agent RL. This review aims to provide researchers, practitioners, and policymakers with a comprehensive understanding of the potential of RL for enhancing solar radiation prediction and to guide future research efforts towards more accurate and reliable renewable energy forecasting systems.

Keywords: Artificial intelligence · Reinforcement learning · Renewable energy · Solar radiation prediction · Systematic review

1 Introduction

Solar energy represents a compelling option as a renewable and environmentally friendly energy source, harnessing the sun's abundant and inexhaustible power [1]. With growing concerns about climate change and the finite nature of fossil fuel reserves, there's been a global momentum towards embracing renewable energy technologies, with solar energy leading the charge towards a greener energy landscape [2]. In contrast to conventional energy sources, solar energy production generates minimal greenhouse gas emissions, offering a viable solution to reducing dependence on fossil fuels and mitigating their

Y. Farhaoui (Ed.): BDBI 2024, ISEM 6, pp. 9–21, 2024.
https://doi.org/10.1007/978-3-031-65018-5_2

detrimental environmental impacts [3]. Additionally, the versatility of solar energy systems enables their deployment in a wide range of settings, from urban areas to remote regions without access to traditional power grids, ensuring accessibility and adaptability to diverse energy requirements.

Amidst growing interest in solar energy optimization, stakeholders are addressing technical, economic, and regulatory challenges [4]. Efforts extend beyond technology to include policy incentives and innovative financing models [5]. Collaboration between governments, research institutions, and industry aims to unlock solar energy's full potential for sustainability and affordability [6].

Accurate solar radiation prediction is essential for optimizing solar energy systems, enabling better planning and utilization of solar resources [7]. Reliable forecasts assist power plant operators in anticipating energy production fluctuations and optimizing panel placement [7, 8]. Moreover, precise prediction supports advanced energy management strategies like demand response and grid balancing, enhancing overall system efficiency and cost-effectiveness [7, 8].

However, traditional prediction methods face limitations that hinder their accuracy and reliability [9]. Statistical models and numerical weather predictions may need help accurately capturing solar radiation dynamics, particularly in regions with variable weather or terrain [9]. These methods can be computationally intensive and rely on sparse weather station data, limiting real-world applicability [9]. Consequently, alternative approaches are needed to provide more reliable solar radiation forecasts for effective energy planning [9].

Reinforcement learning (RL) offers a promising solution for solar radiation prediction by autonomously learning optimal decision-making policies in dynamic environments [10]. Unlike traditional methods relying on pre-defined models or historical data, RL algorithms adapt to changing conditions through environmental interactions [10]. Operating on trial-and-error principles, RL agents learn to maximize rewards while minimizing undesired outcomes, making them suitable for capturing complex solar radiation patterns [10]. RL algorithms can adjust real-time predictive models based on environmental feedback, enhancing system accuracy and reliability [11].

This paper presents a comprehensive review of reinforcement learning techniques for improving solar radiation prediction, offering insights into their applications, challenges, and future directions in optimizing solar energy systems. It outlines the background of solar energy systems, discusses challenges with traditional prediction methods, and highlights reinforcement learning as a promising alternative. The review identifies future research directions to advance solar radiation prediction and renewable energy forecasting by categorizing existing literature based on various criteria.

2 Fundamentals of Reinforcement Learning

Reinforcement Learning (RL) is a distinct branch within machine learning, focusing on training intelligent agents to navigate sequential decision-making tasks within dynamic environments. Unlike supervised learning, where models learn from labeled data, or unsupervised learning, which uncovers patterns within data, RL operates in an interactive setting without explicit instructions. The core objective in RL is for agents to learn optimal actions to maximize cumulative rewards over time [12]. This paradigm finds applications across various domains, from gaming and robotics to recommendation systems, owing to its adaptability and ability to learn from experience [12].

At the heart of RL lies the concept of an agent interacting with an environment, making sequential decisions to maximize cumulative rewards. This process resembles a cycle of trial and error, where the agent explores different actions and learns from their outcomes. The agent refines its decision-making strategy through continuous interaction, striving to achieve the highest possible reward [11]. This interactive nature distinguishes RL from other learning paradigms, as agents actively shape their behavior based on environmental feedback, as demonstrated in Fig. 1.

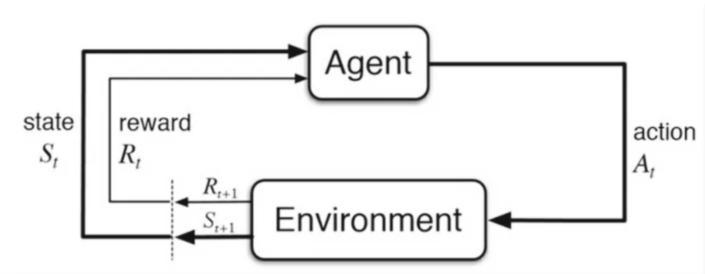

Fig. 1. A graphical representation illustrating the interaction between an agent and its environment in a RL system.

RL has demonstrated remarkable success in numerous domains, showcasing its versatility and effectiveness. RL algorithms have achieved groundbreaking results in gaming, such as AlphaGo's victory over world-class Go players and agents mastering complex video games. Robotics benefits greatly from RL, allowing robots to adapt and learn from their surroundings, whether by navigating through obstacles or refining motor skills. Additionally, RL powers recommendation systems on platforms like Netflix and Amazon, where personalized suggestions enhance user experiences by learning from user interactions. These examples underscore RL's pivotal role in solving real-world problems through adaptive decision-making and continuous learning [13].

3 Traditional Methods for Solar Radiation Prediction

Traditional solar radiation prediction methods encompass various techniques, including statistical models, numerical weather prediction (NWP), and machine learning approaches. Statistical models often rely on historical weather data to infer relationships between meteorological variables and solar radiation levels. These models, such as the Angstrom-Prescott model, estimate solar radiation based on empirical formulas derived from observed weather patterns [14]. Similarly, NWP models simulate atmospheric processes to forecast weather conditions, including solar radiation, over time intervals ranging from hours to days. These models incorporate complex physical equations and meteorological data to predict solar radiation levels at specific locations. Machine learning approaches, such as support vector machines (SVMs) and artificial neural networks

(ANNs), leverage historical data to learn nonlinear relationships between input variables and solar radiation, allowing for more accurate predictions [14].

However, traditional solar radiation prediction methods have several limitations that hinder their accuracy and reliability. Statistical models and empirical formulas may need help to capture the intricate spatial and temporal variations in solar radiation, particularly in regions with diverse topography or weather patterns. NWP models, while capable of simulating complex atmospheric dynamics, often require extensive computational resources and high-resolution input data, limiting their practical utility for real-time applications. Furthermore, machine learning approaches may encounter challenges related to overfitting, data scarcity, and interpretability, especially when dealing with sparse or noisy datasets. These limitations underscore the need for alternative approaches to address traditional methods' shortcomings and provide more robust and efficient solutions for solar radiation prediction [15].

The shortcomings of traditional methods highlight the importance of exploring alternative approaches to improve the accuracy and reliability of solar radiation prediction. One promising avenue is the integration of advanced data-driven techniques, such as deep learning and ensemble learning, which can capture complex nonlinear relationships in solar radiation data more effectively. Examples of such methods include:

- **Convolutional neural networks (CNNs) for spatial data analysis** [16–18].
- **Recurrent neural networks (RNNs) for temporal sequence modeling** [19–21].
- **Ensemble learning methods, such as random forests and gradient boosting, for combining multiple models to improve prediction accuracy** [22–24].

These advanced techniques offer the potential to enhance the predictive performance of solar radiation models by leveraging the strengths of deep learning and ensemble learning algorithms. By embracing these methods, researchers can develop more robust and adaptive models for solar radiation prediction, ultimately contributing to more effective renewable energy planning and management strategies.

4 Reinforcement Learning for Solar Radiation Prediction: State-of-the-Art

Accurately predicting solar radiation is crucial for optimizing solar energy systems, but it remains challenging due to complex atmospheric dynamics. There's been increasing interest in using reinforcement learning (RL) techniques to address this. RL empowers intelligent agents to make sequential decisions in dynamic environments, maximizing cumulative rewards over time. This paper systematically reviews the latest RL applications for solar radiation prediction, shedding light on methodologies, algorithms, and challenges in this rapidly evolving domain.

Our review methodology involved conducting a comprehensive search of relevant literature using the Scopus database, focusing on papers published between 2018 and 2024.

$$\text{TITLE} - \text{ABS (solar radiation AND Reinforcement Learning)} \quad (1)$$

The search query presented in (1) identifies research articles and conference papers on applying RL techniques for solar radiation prediction. Among the 25 documents, comprising 14 articles and 7 conference papers, 4 conference reviews were identified as presented in Fig. 2. However, as conference reviews are typically part of whole conference proceedings and may not provide original research findings, they will be excluded from the study. After retrieving the initial set of papers, we categorized them based on the algorithms, methods, or types of RL employed. Subsequently, we analyzed and synthesized the findings from each paper to provide a systematic overview of the current state-of-the-art reinforcement learning for solar radiation prediction. Through this review, we aim to elucidate the potential of RL techniques in advancing solar energy systems' accuracy, reliability, and efficiency, thereby contributing to the sustainable transition towards renewable energy sources.

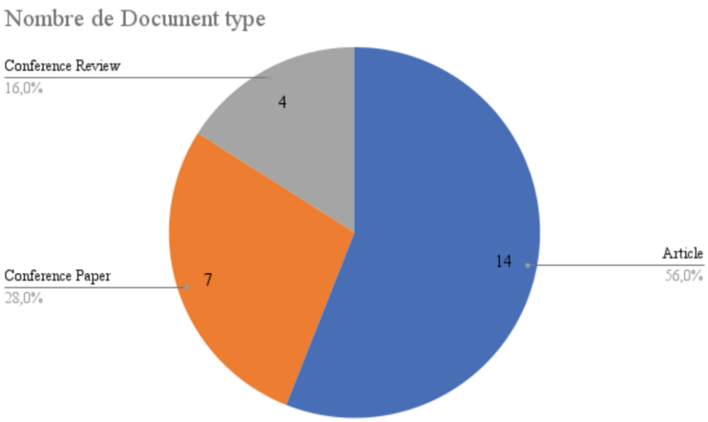

Fig. 2. The distribution of document types among the 25 identified papers

In our systematic review of the state-of-the-art applications of reinforcement learning (RL) for solar radiation prediction, we categorized the identified papers based on the algorithms, methods, or types of RL employed and the specific applications or domains addressed as presented on the next subsections. This categorization allows for a structured analysis of the diverse approaches and methodologies utilized in the field, providing valuable insights into the current trends and advancements.

4.1 Deep Reinforcement Learning

This group comprises papers that leverage deep reinforcement learning (DRL) techniques to address solar energy systems optimization and environmental modeling challenges. DRL, which utilizes deep neural networks to approximate complex functions and learn representations directly from raw input data, has shown promise in optimizing the efficiency of renewable energy production and enhancing resource management in agricultural settings.

Heckmann, R et al. [25] investigate the decarbonization potential of hydrogen for the heating industry, focusing on optimizing the efficiency of green hydrogen production using deep reinforcement learning (DRL). The study simulates a hydrogen production plant comprising various components, such as photovoltaic panels, an electrolyzer, and hydrogen storage, to optimize the plant's operation and heat supply using DRL techniques. The findings demonstrate the competitive production of hydrogen derived from renewable or stored energy sources for the heating industry, highlighting the potential of DRL in enhancing renewable energy systems.

Cena, C et al. [26] explore applying DRL techniques for under-actuated attitude control of satellites, leveraging solar radiation pressure (SRP) to perform reaction wheel desaturation and attitude control autonomously. The study proposes a model-free DRL approach to learn the optimal control policy for satellite attitude control, considering the disturbances caused by SRP. Simulation results demonstrate the effectiveness and robustness of the proposed approach in maintaining desired attitudes and performing desaturation operations, showcasing the potential of DRL in autonomous spacecraft operations.

Sharma G et al. [27] introduce DeepEvap, an ensemble approach based on DRL techniques, for estimating reference evapotranspiration (ET0) in precision agriculture. The study utilizes deep neural network models and a DRL approach to estimate ET0 values using meteorological data inputs. Results demonstrate DeepEvap's competitive performance in ET0 prediction, outperforming baseline models and existing ensemble approaches. The findings highlight the potential of DRL in improving resource management and enhancing agricultural productivity through accurate ET0 estimation.

These papers demonstrate the diverse applications of DRL techniques in optimizing renewable energy systems, spacecraft operations, and agricultural resource management. By leveraging deep neural networks and reinforcement learning algorithms, these studies advance the efficiency, reliability, and sustainability of various domains reliant on solar energy and environmental modeling.

4.2 Meta-reinforcement Learning

This group encompasses papers that investigate the application of meta-reinforcement learning (MRL) techniques for autonomous guidance and control of spacecraft during impact missions towards binary asteroid systems. MRL, which enables agents to adapt their learning processes to new tasks or environments, is leveraged to develop control policies for maneuvering spacecraft with low thrust during the terminal phase of impact missions. These papers utilize convolutional-recurrent neural networks to map optical observations collected by onboard cameras to optimal control thrust and thrusting times, training the networks using reinforcement learning algorithms.

Federici L et al. [28] focus on applying meta-reinforcement learning for the autonomous guidance of a spacecraft during the terminal phase of an impact mission toward a binary asteroid system. The control policy is replaced by a convolutional-recurrent neural network, which maps optical observations to control thrust and thrusting times. The network is trained using reinforcement learning methods, with the final phase of NASA's Double Asteroid Redirection Test (DART) mission as a test case. Numerical results demonstrate the guidance system's effectiveness in driving the spacecraft toward the final impact point in most test scenarios.

Federici L. et al. [29] explore using meta-reinforcement learning for the autonomous guidance of a spacecraft with low thrust during the terminal phase of an impact mission towards a binary asteroid system. The control policy is replaced by a convolutional-recurrent neural network, trained using Proximal Policy Optimization, a policy-gradient reinforcement learning algorithm. The study utilizes the final phase of the DART mission as a test case, aiming to maneuver the spacecraft to impact the smaller object in the binary system. Numerical results demonstrate the guidance system's capability to drive the spaceship toward the final impact point in nearly all test scenarios.

In conclusion, the papers within the Meta-Reinforcement Learning group showcase the efficacy of meta-reinforcement learning (MRL) techniques in enabling autonomous guidance and control of spacecraft during impact missions towards binary asteroid systems. By leveraging convolutional-recurrent neural networks and reinforcement learning algorithms, these studies demonstrate the feasibility of training control policies that map optical observations to optimal thrust and thrusting times. The results highlight the potential of MRL in enhancing spacecraft autonomy and precision in navigating complex space environments. Further research in this domain could focus on extending MRL methodologies to address additional challenges in space exploration missions, ultimately advancing our capabilities for autonomous space navigation and exploration.

4.3 General Reinforcement Learning

Within this category, papers are further sub-grouped based on specific applications or domains:

- **Solar Energy Systems Optimization**
  This subgroup focuses on leveraging reinforcement learning (RL) techniques to optimize the operation of solar energy systems, enhancing energy efficiency and performance.

  Correa-Jullian C et al. [30] employ an RL tabular Q-learning framework to optimize operation schedules for a solar hot water system. Key performance indicators serve as rewards for balancing energy efficiency, heat-load delivery, and operational costs. Results show dynamic schedule optimization based on varying meteorological conditions, prioritizing efficient energy source utilization, leading to up to 21% performance improvements. Chen Y. et al. [31] introduce an RL control strategy, employing model-free Q-learning to minimize energy consumption and thermal discomfort in HVAC and window systems. The system evaluates outdoor and indoor environmental factors and responds with control decisions targeting immediate and long-term goals. Simulation results demonstrate significant energy savings and reduction in discomfort degree hours compared to heuristic control strategies, highlighting the efficiency of RL-based optimization in natural ventilation systems.
- **Renewable Energy Planning and Management**
  Researchers in the Renewable Energy Planning and Management subgroup investigate methods for optimizing renewable energy utilization in energy management systems. These studies explore strategies for coordinating energy demand among households, electric vehicles (EVs), and smart microgrid (MG) elements while efficiently managing uncertainties associated with renewable energy generation. By

applying reinforcement learning (RL) algorithms, these papers aim to schedule energy demand effectively, incorporate uncertainty, and reduce power consumption costs, contributing to sustainable energy management practices.

Almughram, O et al. [32] explore a Reinforcement Learning Approach for integrating an Intelligent Home Energy Management System (HEMS) with a Vehicle-to-Home Unit (V2H). The study investigates the impact of renewable energy sources, such as solar photovoltaic panels, wind turbines, and electric vehicles (EVs), on maximum solar radiation hours. A Reinforcement Learning Home Centralized Photovoltaic (RL-HCPV) scheduling algorithm is developed to manage energy demand between smart micro-grid elements, considering uncertainties. Simulation results demonstrate the RL-HCPV system's ability to efficiently handle demand response, incorporate uncertainty, and reduce power consumption costs with sustainable power production, showcasing the advantages of RL and V2H technology in smart building storage. Wang L et al. [33] focus on optimal charging profile design for solar-powered self-sustainable UAV communication networks, accounting for the day-scale time-variability of solar radiation and user service demand. The study formulates the problem into a time-coupled mixed-integer non-convex optimization problem and designs deep reinforcement learning (DRL) algorithms to address the challenge. Simulation results illustrate the efficacy of the DRL algorithms in trading off communication performance against net energy loss, providing insights into parameter impacts on tradeoff performance.

- **Environmental Modeling and Prediction**
  In this subgroup, researchers investigate the application of reinforcement learning (RL) techniques for modeling and predicting environmental factors, mainly focusing on solar irradiance and heat flux variability.

  Shikhola, T et al. [34] present a study on seasonal solar irradiance prediction using a modified fuzzy Q-learning approach. The research focuses on leveraging reinforcement learning techniques to enhance the accuracy of solar irradiance forecasts, particularly on a seasonal timescale. By integrating fuzzy logic principles with Q-learning algorithms, the study aims to improve prediction performance, thereby contributing to more efficient utilization of solar energy resources. Jeon B. et al. [35] investigate solar irradiance prediction using reinforcement learning pre-trained with limited historical data. The paper addresses the challenge of accurately predicting solar irradiance, especially in scenarios with limited historical data. By employing reinforcement learning models pre-trained with available data, the study explores methods to enhance the reliability of solar irradiance forecasts, which is crucial for optimizing solar energy generation and utilization. Bonasera, S. et al. [36] focus on designing Sun–Earth L2 Halo Orbit Stationkeeping Maneuvers via Reinforcement Learning. The research aims to develop efficient control strategies for maintaining spacecraft orbits around the Sun-Earth Lagrange point L2. By applying reinforcement learning techniques, the study seeks to optimize stationkeeping maneuvers, ensuring the stability and longevity of spacecraft operations in such orbits. Chen C et al. [37] introduce CuRL, a Generic Framework for Bi-Criteria Optimal Path-Finding Based on Deep Reinforcement Learning. The paper presents a versatile framework for optimizing path-finding tasks, considering multiple criteria simultaneously. By integrating deep reinforcement learning methods, CuRL offers a flexible and efficient solution for navigating complex environments, with applications ranging from robotics to environmental monitoring. Habeeb F. et al. [38] propose Dynamic Data Streams for Time-Critical IoT Systems in Energy-Aware IoT Devices Using Reinforcement Learning. The study explores using reinforcement learning algorithms to manage dynamic data streams in energy-aware Internet of Things (IoT) devices. By adapting RL techniques to handle time-critical IoT systems, the research aims to improve energy efficiency and responsiveness, enhancing the overall performance of IoT applications in energy management. Banerjee S et al. [39] present Deep reinforcement learning for variability prediction in latent heat flux from low-cost meteorological parameters. The paper investigates the application of deep reinforcement learning for predicting variability in latent heat flux using inexpensive meteorological parameters. By leveraging RL techniques, the study aims to improve the accuracy of latent heat flux predictions, which are essential for various environmental modeling and agricultural applications.

- **Urban Planning and Energy Efficiency**
  Urban Planning and Energy Efficiency subgroup researchers explore the intersection of urban design, energy efficiency, and environmental sustainability. These studies aim to optimize urban planning strategies, enhance energy performance, and promote renewable energy utilization in urban environments by employing reinforcement learning techniques.

  Chang S. et al. [40] investigate the multivariate relationships between campus design parameters and energy performance using reinforcement learning and parametric modeling. The study analyzes the complex interactions between various design elements and their impact on energy consumption in campus environments. Through reinforcement learning and parametric modeling approaches, the research aims to identify optimal design configurations that minimize energy usage while maintaining functionality and aesthetics. Chang S. et al. [41] present generative design and performance modeling for exploring relationships between urban built forms, sky opening, solar radiation, and energy. The paper examines the potential of generative design techniques and performance modeling to inform urban planning decisions related to solar energy integration and energy-efficient building design. By leveraging reinforcement learning methods, the study seeks to generate design solutions that maximize solar radiation exposure while minimizing energy demand, contributing to sustainable urban development practices.

5 Challenges, Limitations, and Future Directions

In the pursuit of harnessing reinforcement learning for enhanced solar radiation prediction, several challenges and limitations emerge, shaping the future trajectory of research in this domain. One significant challenge lies in the complexity and dynamic nature of the solar energy system itself. Solar radiation prediction involves intricate interactions between atmospheric, geographical, and meteorological factors, introducing inherent uncertainties and nonlinearities. Addressing these complexities requires robust models and algorithms capable of accurately capturing the intricate dynamics of solar radiation.

Furthermore, data scarcity remains a pervasive challenge in solar radiation prediction, particularly in regions with limited monitoring infrastructure or historical data availability. This scarcity impedes the development and training of reinforcement learning models, which rely heavily on extensive and diverse datasets for effective learning and generalization. Overcoming data scarcity demands innovative approaches for data augmentation, transfer learning, or the integration of domain knowledge to supplement existing datasets and improve model performance.

Looking ahead, future research directions in reinforcement learning for solar radiation prediction are promising yet multifaceted. Firstly, advancements in algorithmic development and model architectures are imperative to enhance reinforcement learning models' predictive accuracy and robustness. Incorporating novel techniques such as meta-learning, ensemble methods, or hybrid models that integrate reinforcement learning with other machine learning paradigms could significantly improve solar radiation prediction accuracy. Additionally, there is a growing need for interdisciplinary collaborations bridging the gap between domain experts in solar energy and machine learning researchers. Such collaborations can facilitate the development of tailored solutions that effectively address the unique challenges and requirements of solar radiation prediction, paving the way for more sustainable and efficient solar energy systems.

6 Conclusion

In conclusion, this comprehensive review has shed light on the state-of-the-art applications of reinforcement learning in solar radiation prediction. Through an in-depth analysis of various research papers, we have explored the diverse methodologies, algorithms, and applications employed to harness the power of reinforcement learning to enhance solar energy systems. From deep reinforcement learning approaches to meta-reinforcement learning techniques, each method offers unique advantages and insights into optimizing solar radiation prediction for improved efficiency and sustainability.

Moreover, the review has highlighted the significant contributions of these studies in addressing critical challenges and limitations in solar radiation prediction, such as data scarcity, model complexity, and algorithmic robustness. By leveraging reinforcement learning algorithms, researchers have made significant strides in overcoming these hurdles and advancing the state-of-the-art in solar energy system optimization. However, there remains ample room for further exploration and innovation, particularly in integrating interdisciplinary expertise, addressing real-world deployment challenges, and scaling up these solutions for broader impact. The insights from this review serve as a valuable foundation for future research endeavors in the intersection of reinforcement learning and solar energy systems. By fostering collaboration, innovation, and knowledge exchange across disciplines, we can collectively drive the development of sustainable and efficient solar energy solutions, paving the way towards a greener and more sustainable future.

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