electronics

Review

Energy Prediction for Energy-Harvesting Wireless Sensor: A Systematic Mapping Study

Zhenbo Yuan [1], Yongqi Ge [1,*], Jiayuan Wei [2], Shuhua Yuan [1], Rui Liu [1] and Xian Mo [1]

[1] School of Information Engineering, Ningxia University, Yinchuan 750014, China; yuanzb98@stu.nxu.edu.cn (Z.Y.); shuayuan@stu.nxu.edu.cn (S.Y.); ruiliu@nxu.edu.cn (R.L.); mxian168@nxu.edu.cn (X.M.)
[2] College of Electronics and Information Engineering, Tongji University, Shanghai 201804, China; jywei@tongji.edu.cn
* Correspondence: geyongqi@nxu.edu.cn; Tel.: +86-189-9508-1013

Abstract: Energy prediction plays a significant role in energy-harvesting wireless sensors (EHWS), as it helps wireless sensors regulate their duty cycles, achieve energy neutrality, and extend their lifespan. To explore and analyze advanced technologies and methods regarding energy prediction for EHWS, this study identifies future research directions and addresses the challenges faced based on the current research status, assisting with future literature research. This scholarly inquiry delineates future research prospects and addresses prevailing challenges within the context of the extant research landscape, thereby facilitating prospective scholarly endeavors. This study employed the systematic mapping study (SMS) approach to screen and further investigate the relevant literature. After searching and screening for papers from the ACM, IEEE Xplore, and Web of Science (WOS) databases from January 2007 to December 2022, 98 papers met the requirements of this study. Subsequently, the SMS was conducted for five research questions. The results showed that the solution proposal type category had the largest proportion among all research types, accounting for 58% of the total number, indicating that the research focusing on this field is placed on improving the existing methods or proposing new ones. Additionally, based on the SMS analysis, this study provides a systematic review of the technical utilization and improvement approaches, as well as the strengths and limitations of the selected prediction methods. Furthermore, by considering the current research landscape, this paper identifies the existing challenges and suggests future research directions, thereby offering valuable insights to researchers for making informed decisions regarding their chosen paths. The significance of this study lies in its contribution to driving advancements in the field of energy-harvesting wireless sensor networks. The importance of this study is underscored by its contribution to advancing the domain of energy-harvesting wireless sensor networks, thereby serving as a touchstone for forthcoming researchers in this specialized field.

Keywords: wireless sensor; energy harvesting; energy prediction; SMS

check for updates

Citation: Yuan, Z.; Ge, Y.; Wei, J.; Yuan, S.; Liu, R.; Mo, X. Energy Prediction for Energy-Harvesting Wireless Sensor: A Systematic Mapping Study. *Electronics* **2023**, *12*, 4304. https://doi.org/10.3390/electronics12204304

Academic Editor: Dimitris Kanellopoulos

Received: 8 September 2023
Revised: 13 October 2023
Accepted: 16 October 2023
Published: 18 October 2023

1. Introduction

In recent years, wireless sensor networks have been widely used in fields such as biomedicine [1], environmental monitoring [2], and the military [3]. As the fundamental building blocks of wireless sensor networks, wireless sensors are primarily responsible for tasks such as data collection, processing, and transmission. Wireless sensors typically use batteries as a power supply, but many systems require long uninterrupted operation, and the limited capacity of batteries severely restricts the performance of the system. Once the battery is depleted, the sensor ceases to function, necessitating battery replacement. However, a substantial number of wireless sensor nodes are deployed in harsh or inaccessible environments, making battery replacement costly or even infeasible. To address this challenge, a method has been proposed to supplement or even replace the battery: energy harvesting from the environment. Energy-harvesting technology enables sensor nodes to acquire energy from the surrounding environment, such as solar, wind, thermal, and vibrational energy, and convert it into electrical energy. This enables the sensor nodes to operate continuously without the need for battery replacement, thereby avoiding node failure. The wireless sensor nodes powered by energy-harvesting techniques will be referred to as energy-harvesting wireless sensors (EHWS) in this paper.

The harvested environmental energy exhibits non-linear dynamic variations over time, leading to situations of energy waste or inadequacy in EHWS. To ensure sustainable sensor operation, the ideal scenario is for the energy harvested by the energy-harvesting unit to consistently match the energy consumed by the energy consumption unit, achieving energy-neutral operation (ENO) [4]. However, in practical situations, the energy harvested by the energy-harvesting unit may surpass or fall short of the energy consumed by the energy-consumption unit. Therefore, accurate energy prediction is crucial for maintaining the energy-neutral state of EHWS.

Energy-harvesting wireless sensor networks have found numerous application scenarios, and researchers have extended their investigations in various directions. In [5], this study proposes a novel opportunistic data collection mechanism by combining software-defined mobile aggregation and EHWS (energy-harvesting wireless sensor) networks. The research aims to utilize SDMS (software-defined mobile sensor) and WSN (wireless sensor network) for event monitoring in smart grids, to achieve superior energy management. Simulation experiments conducted using the EstiNet 9.0 network simulation tool indicate that, compared to existing research, the designed approach significantly improves data transmission efficiency and reduces data packet corruption, memory overflow, latency, and energy consumption, thus extending the network's lifespan. In [6], an algorithm for cluster head (CH) repositioning is introduced based on the assumption of selfish clusters to prolong the lifetime of wireless sensor networks. By combining mobile and solar-powered cluster heads with energy harvesting, the objective is to reduce the overall energy consumption in the network and extend its lifespan. The algorithm repositions the CHs to their centroids in each round based on the selfish cluster assumption. Simulation results demonstrate the algorithm's advantages in extending network lifespan and stabilizing its performance. In [7], an opportunistic data collection mechanism that combines energy harvesting with wireless sensor networks is presented. By integrating software-defined mobile aggregation, wireless sensor networks, and energy harvesting, the research aims to monitor events in smart grids to achieve efficient energy management. Through simulation experiments, the study's results show significant improvements compared to existing research in data transmission efficiency, data packet integrity, memory usage, latency, and energy consumption, ultimately extending the network's lifespan.

To gain a deep understanding of the current research status and the latest developments in the research field and provide the theoretical support required by subsequent researchers, a literature review method needs to be adopted to conduct a thorough and effective summary of the field. Currently, researchers have proposed some convenient and effective literature review methods, including systematic literature review (SLR) [8], systematic mapping study (SMS) [9], and systematic review (SR) [10]. An SMS is a method for categorizing and summarizing the literature in a specific thematic area. It can provide a comprehensive and objective perspective on the thematic area, help identify research trends, research gaps, and future research directions, and provide guidance for subsequent SLR or other research. The classification results are usually processed graphically and can provide a visual representation of the results. Given the advantages of the SMS method, this study opted to employ it for conducting a comprehensive review of the research domain. This approach enables a comprehensive understanding of the current state and trends within the field, providing valuable guidance and insights for subsequent research endeavors.

In contrast to conventional literature review methods, which may lack systematic filtering mechanisms, relying solely on individual reading and judgment for the selection of literature, there is the potential for these approaches to introduce bias or omit critical scholarly works [11–14]. The systematic literature review (SLR) method, denoted as SMS, adheres to a structured process to ensure that the reviewed literature maintains a high degree of relevance and aligns with the thematic requirements. Initially, the SMS method hinges upon the formulation of key search terms, specifically designed to explore literature pertinent to a particular research domain. By employing these key search terms, the SMS method conducts searches within selected literature databases, retrieving potential literature resources closely related to the research domain. Building upon the retrieved articles, the SMS method engages in a sequence of rigorous filtration and analysis procedures. These processes may involve the extraction of essential bibliographic data, including publication year, authorship, and keywords, for further research and review purposes. The systematic workflow and key term-based retrieval in the SMS method contribute to enhancing the accuracy and comprehensiveness of the literature review. In comparison to methods relying on individual reading and subjective judgment, the SMS method offers heightened credibility within the realm of academic research.

1.1. Main Contributions

The main contributions are as follows: This paper uses an SMS to study energy-prediction methods for EHWS, identify the research evidence on this topic, and present quantitative results. This study is carried out to answer five different research questions on energy prediction. Through a brief analysis of the literature, the current research status within the field is extensively discussed, along with the challenges currently faced and future research directions. This provides researchers with important guidance and insights, and this work provides researchers with a research overview of the practice in this field over the past 17 years.

This review aims to categorize and organize the literature in the field of EHWS energy prediction, to provide researchers with a comprehensive overview of this domain. This will enable them to quickly identify research hotspots, guide their research directions, and assist them in defining the research focal points and future development trends in the field of energy-harvesting wireless sensor networks.

1.2. Organization

The rest of the paper is organized as follows: Section 2 describes the SMS. Section 3 presents the research results and answers the research questions. Data analysis and visualization are presented in Section 4, and in Section 5, this study analyzes and describes the current state of the research on some prediction methods. Section 6 analyzes the challenges and prospects in this field. Finally, Section 7 provides a summary.

2. System Mapping Process

This section provides an overview of the systematic mapping process employed in the review of energy-prediction methods for EHWS. The process, as shown in Figure 1 [15], consists of the following five steps: (1) identifying the research questions to determine the scope of literature search; (2) conducting preliminary searches to identify all relevant papers; (3) filtering the identified papers based on relevance to the research area; (4) reading the selected papers and proposing a corresponding classification scheme; and (5) categorizing all papers according to the classification scheme and presenting the analysis results of each category through data visualization in the form of a map. Each step generates a result, and the outcome is a system map. Through the systematic mapping process, this study classifies and synthesizes various energy-prediction methods, thereby establishing a comprehensive and structured knowledge framework.

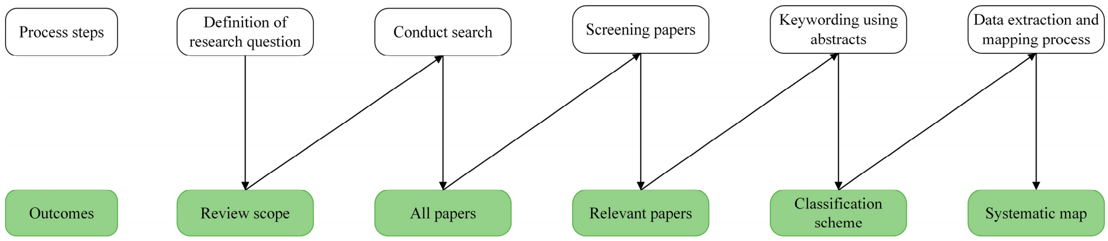


Figure 1. The steps of a systematic mapping study.

2.1. Research Problems

Based on SMS, the overall goal of this study is to identify the types of research, energy types, prediction methods, tools, methods, and publication types related to energy-prediction algorithms in EHWS since 2007. The following is a detailed description of the issues of concern:

RQ1: What types of research have been conducted on EHWS since 2007?

This study will use an SMS to determine the classification and the popular research trends in the field of energy prediction algorithms for EHWS.

RQ2: What are the types of predicted energy?

This study will classify the selected papers based on the predicted energy types and perform a data analysis based on the actual classification results.

RQ3: What types of prediction methods are used in EHWS energy-prediction algorithms?

In related research issues, many researchers have adopted different types of prediction methods. The focus of this study is to determine the common approaches used by most researchers in the related field.

RQ4: How many tool papers and method papers are proposed in the research?

Tool papers and method papers are important publication types in the scientific research field. The goal of this study is to identify those papers based on tools and methods that can be used in future studies.

RQ5: How were the papers published?

This study focuses on the publishers, the publication year of the papers, and the types of publications.

2.2. Research Search and Screening

During the period from January 2007 to December 2022, a comprehensive search was conducted in the IEEE, ACM, and WOS databases using the keyword combination "(Energy harvesting) AND (Wireless sensor) AND (Prediction or Forecast) AND (application OR tool OR method)". This search yielded a total of 5862 relevant research papers. Subsequently, a selection process was carried out based on the inclusion and exclusion criteria outlined in Table 1. Based on the SMS standards and the practical context of EHWS energy prediction, this study has formulated three inclusion criteria to ensure the selection of the literature that aligns with the focus of this research. These three criteria are as follows: (1) The literature must provide novel theoretical approaches for EHWS energy prediction. (2) The literature must enhance existing methods in the field of EHWS energy prediction. (3) The literature must validate and evaluate the methods already proposed in the EHWS energy-prediction domain.

Table 1. Inclusion and Exclusion criteria.

Inclusion Criteria	Exclusion Criteria
(1) The paper provides new theoretical methods. (2) The paper improves methods for the EHWS energy-prediction field. (3) The paper verifies and evaluates the methods used in the research field.	(1) The paper is not in English. (2) The paper is a poster or book. (3) The search pertains to a patent. (4) The paper only introduces the EHWS system. (5) The prediction algorithm is not applied to EHWS.

Simultaneously, to exclude irrelevant literature that might not be pertinent to the study, this research has established five exclusion criteria, as follows: (1) The literature must be in English since this study is exclusively concerned with English-language literature. (2) The literature must not be in the form of posters or books; only conference or journal papers are eligible. (3) The literature must not be patented. (4) The literature must encompass an introduction to EHWS systems and must utilize energy-prediction methods. (5) The prediction methods discussed in the literature must have been applied to EHWS. These criteria will ensure the quality and relevance of the selected literature.

Initially, the first round of screening involved reading the titles and abstracts to determine the relevance of each paper to the research topic. As a result, 125 papers were identified for further consideration. These selected papers underwent a second round of screening, involving a thorough examination of the full text, resulting in the retention of 78 papers. Furthermore, the snowball method [16] was employed to supplement the second round of screening, leading to the discovery of an additional 20 papers. Through a series of rigorous screening stages, a final set of 98 papers was ultimately chosen as the focal point of this study. The specific steps of the selection process are illustrated in Figure 2.

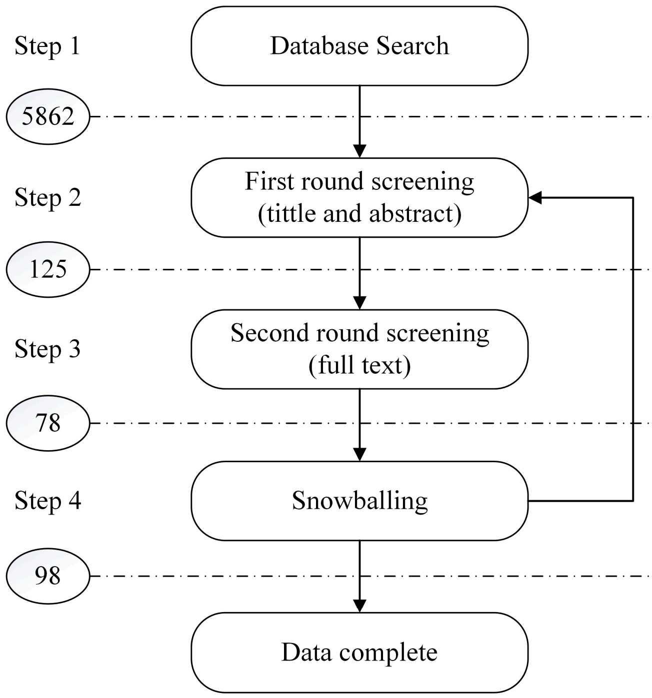


Figure 2. Database search and paper screening process.

3. Research Classification

After screening the papers, this study classified the studies according to the abstracts and keywords of the relevant papers. Following the classification guidelines provided by Peterson et al. [17], this paper divided the studies into five categories to address different research questions.

3.1. Classification of Research Types

This study classified the selected papers according to the paper classification framework proposed by Wieringa et al. [18]. According to this classification framework, research types (RT) can be divided into six categories: solution proposal papers, validation research papers, experience papers, evaluation research papers, opinion papers, and philosophical papers.

Solution proposal papers represent a type of research that improves or develops new technologies based on existing solutions. Validation research papers do not require the design of experiments, analysis processes, or a discussion of the results regarding a laboratory environment or practice. Experience papers provide a detailed description of personal experiences with relevant technologies, tools, or methods. Evaluation research papers aim to evaluate the process and final results of research work in practice. Opinion papers reflect the authors' personal evaluation opinions on technologies, experiments, tools, or methods in a research field. Finally, philosophical papers discuss new theoretical systems or new methods of demonstrating existing things.

3.2. Classification of Energy Types

This study classified energy types according to different characteristics, placing these into five categories: solar energy, wind energy, vibration energy, heat energy, and radio frequency (RF). The characteristics of each energy type are plotted in Table 2.

Table 2. Different types of energy and characteristics.

Energy Types	Characteristics
Solar energy	Renewable, Widely distributed, Non-polluting, Harvestable.
Wind energy	Accessible, Emission-free, Uncertain of change, Adaptable.
Vibration energy	Diverse vibration sources, Capture of low-frequency vibration, Power transfer, Vibration conversion
Heat energy	Temperature difference drive, Heat conduction, Heat energy conversion.
Radiant energy	Electromagnetic wave propagation, Wide spectrum range, No media transmission

3.3. Classification of Prediction Methods

According to the prediction methods (PM) and characteristics used in the selected papers, this study divided them into the following three categories, and their respective characteristics are presented in Table 3:

Table 3. Classification of prediction methods and their characteristics.

Prediction Methods	Characteristics
Machine learning (ML)	Complicated calculation, Requires large amounts of data, Relatively high accuracy, Suitable for complex systems.
Model-free (MF)	Simple calculation, No model building required, Dependent on data quality, Relatively low accuracy.
Model-based (MB)	Precise modeling, Environmental suitability, Physical constraint, Parameter estimation

Machine learning (ML): Using machine learning methods to make predictions provides high precision but relatively high complexity.

Model-free (MF): Relying solely on energy information harvested in the past for prediction.

Model-based (MB): Modeling the energy-harvesting situation so as not to rely only on the energy information harvested in the past to make predictions.

3.4. Classification of Tools or Methods

If a paper proposes a new prediction method or improvement, it is classified as a method paper. Papers that use energy-prediction technology in their experimental design and practical applications are classified as tool papers.

3.5. Publication Classification

This study categorizes publication information following a general classification scheme, such as publisher, year of publication, and publication type. The publishers are categorized into four types: IEEE, ACM, Springer, ScienceDirect (SD), and Others. The publication years span a total of 17 years, from 2007 to 2022. The publication types (PT) are classified into international journals and international conferences.

3.6. Classification of Energy Types

After reading the selected papers, this study filled in a table based on the research questions. Table 4 presents the responses to the five classification questions posed in this study for the selected 98 relevant articles, arranged in descending order and based on their publication year. The table provides a comprehensive breakdown of the research type, energy type, prediction method, tool or technique, and publication status for each piece of literature, facilitating a clear depiction of the respective categories to which different articles belong.

Table 4. Data extracted from the selected papers.

ID	Ref	RQ1	RQ2	RQ3	RQ4		RQ5	
		RT	**Energy Type**	**PM**	**Tool or Method**	**Year**	**PT**	**Publisher**
1	[19]	Solution	Solar energy	MF	Tool	2022	Journal	IEEE
2	[20]	Validation	Solar energy	ML	Tool	2022	Conference	IEEE
3	[21]	Solution	Solar energy	ML	Method	2022	Conference	IEEE
4	[22]	Solution	Solar energy	ML	Method	2022	Journal	Other
5	[23]	Evaluation	Solar energy	MB	Tool	2021	Journal	ACM
6	[24]	Solution	Solar energy	MF	Method	2021	Conference	IEEE
7	[25]	Solution	Solar energy	MF	Method	2021	Journal	Springer
8	[26]	Solution	Solar energy	MB	Method	2020	Journal	Other
9	[27]	Solution	Solar energy	MB	method	2020	Journal	IEEE
10	[28]	Solution	Solar energy	MB	Method	2020	Journal	Other
11	[29]	Evaluation	Vibrations	MF	Tool	2020	Journal	Other
12	[30]	Evaluation	Solar energy	ML	Tool	2020	Conference	IEEE
13	[31]	Solution	Solar energy	ML	Method	2020	Journal	Springer
14	[32]	Evaluation	Solar energy	ML	Tool	2020	Journal	Springer
15	[33]	Validation	Solar energy	MB	Tool	2019	Journal	SD
16	[34]	Evaluation	Solar energy	MB	Tool	2019	Journal	IEEE
17	[35]	Validation	Solar energy	MB	Method	2019	Conference	IEEE
18	[36]	Solution	RF	MB	Method	2019	Journal	Other
19	[37]	Solution	Solar energy	MF	Method	2019	Journal	IEEE
20	[38]	Validation	Solar energy	MF	Tool	2019	Journal	Other
21	[39]	Solution	Solar energy	MF	Method	2019	Conference	IEEE
22	[40]	Validation	Solar energy	MF	Tool	2019	Conference	IEEE
23	[41]	Solution	Solar energy	ML	Tool	2019	Conference	IEEE
24	[42]	Solution	Solar energy	ML	Method	2019	Conference	IEEE
25	[43]	Validation	Solar energy	ML	Tool	2019	Journal	Springer
26	[44]	Solution	Solar energy	ML	Method	2019	Journal	Other
27	[45]	Solution	Solar/wind	MB	Method	2018	Journal	Other
28	[46]	Solution	Solar energy	MB	Method	2018	Conference	IEEE
29	[47]	Solution	Solar energy	MB	Method	2018	Journal	IEEE
30	[48]	Solution	Wind energy	MB	Method	2018	Journal	IEEE
31	[49]	Validation	Solar energy	MF	Tool	2018	Conference	ACM
32	[50]	Solution	Solar energy	MF	Method	2018	Conference	IEEE
33	[51]	Validation	Solar energy	MF	Tool	2018	Conference	IEEE
34	[52]	Solution	Solar energy	MF	Method	2018	Conference	IEEE
35	[53]	Solution	Solar energy	MF	Method	2018	Journal	Other
36	[54]	Solution	Solar energy	ML	Method	2018	Journal	IEEE
37	[55]	Validation	Solar energy	ML	Method	2018	Journal	SD
38	[56]	Validation	Solar energy	ML	Tool	2018	Conference	IEEE
39	[57]	Solution	Solar energy	MB	Method	2017	Conference	IEEE
40	[58]	Solution	Solar/Wind	MB	Method	2017	Journal	Other
41	[59]	Validation	Solar energy	MB	Tool	2017	Journal	Other
42	[60]	Solution	Solar/Wind	MF	Method	2017	Journal	Other
43	[61]	Solution	Solar energy	MF	Method	2017	Journal	SD
44	[62]	Solution	Wind energy	MB	Method	2017	Journal	SD
45	[63]	Validation	Solar energy	MF	Tool	2017	Conference	IEEE

Table 4. *Cont.*

ID	Ref	RQ1	RQ2	RQ3	RQ4		RQ5	
		RT	**Energy Type**	**PM**	**Tool or Method**	**Year**	**PT**	**Publisher**
46	[64]	Validation	Solar energy	ML	Method	2017	Conference	ACM
47	[65]	Validation	Solar energy	ML	Tool	2017	Conference	IEEE
48	[66]	Solution	Solar energy	MB	Tool	2016	Journal	Other
49	[67]	Experience	Solar energy	MF	Tool	2016	Conference	IEEE
50	[68]	Experience	Solar energy	MF	Tool	2016	Journal	Other
51	[69]	Validation	Wind energy	MF	Tool	2016	Conference	IEEE
52	[70]	Validation	Solar energy	MF	Tool	2016	Journal	IEEE
53	[71]	Solution	Solar/Wind	MF	Method	2016	Journal	IEEE
54	[72]	Solution	Solar energy	ML	Method	2016	Journal	IEEE
55	[73]	Solution	Solar energy	ML	Method	2016	Conference	IEEE
56	[74]	Solution	Solar energy	ML	Method	2016	Conference	ACM
57	[75]	Solution	Solar energy	MF	Tool	2016	Journal	Springer
58	[76]	Validation	Solar energy	ML	Tool	2016	Conference	IEEE
59	[77]	Solution	RF	ML	Tool	2016	Journal	IEEE
60	[78]	Solution	Solar energy	MB	Method	2016	Journal	Other
61	[79]	Solution	Solar energy	MB	Method	2015	Journal	Other
62	[80]	Validation	Solar energy	MF	Tool	2015	Journal	IEEE
63	[81]	Validation	Solar energy	MF	Tool	2015	Conference	IEEE
64	[82]	Evaluation	Solar energy	ML	Tool	2015	Conference	ACM
65	[83]	Solution	Solar energy	ML	Method	2015	Conference	ACM
66	[84]	Solution	Solar energy	ML	Method	2015	Journal	ACM
67	[85]	Evaluation	Solar energy	MF	Tool	2015	Conference	IEEE
68	[86]	Solution	Solar/Wind	MB	Method	2014	Journal	SD
69	[87]	Validation	Solar energy	MB	Tool	2014	Journal	IEEE
70	[88]	Validation	Solar energy	MB	Tool	2014	Journal	IEEE
71	[89]	Experience	Solar energy	MF	Tool	2014	Conference	ACM
72	[90]	Validation	Solar energy	MF	Tool	2014	Conference	ACM
73	[91]	Evaluation	Solar energy	ML	Tool	2014	Journal	IEEE
74	[92]	Solution	Solar energy	ML	Method	2014	Conference	ACM
75	[93]	Solution	Solar/Wind	MB	Method	2013	Conference	IEEE
76	[94]	Solution	Solar energy	MB	Method	2013	Journal	IEEE
77	[95]	Solution	Solar energy	MF	Method	2013	Conference	ACM
78	[96]	Evaluation	Solar energy	MB	Tool	2013	Conference	IEEE
79	[97]	Solution	Solar energy	MB	Method	2012	Conference	ACM
80	[98]	Solution	Solar/Wind	MF	Method	2012	Conference	IEEE
81	[99]	Solution	Solar energy	MF	Method	2012	Conference	IEEE
82	[100]	Experience	Solar energy	MB	Tool	2012	Journal	SD
83	[101]	Validation	Solar energy	MF	Tool	2011	Conference	ACM
84	[102]	Evaluation	Solar energy	MF	Tool	2011	Journal	SD
85	[103]	Solution	Solar/Wind	MB	Method	2010	Conference	IEEE
86	[104]	Evaluation	Solar energy	MF	Tool	2010	Journal	Other
87	[105]	Evaluation	Solar energy	MF	Tool	2010	Conference	IEEE
88	[106]	Evaluation	Solar energy	MF	Method	2010	Conference	IEEE
89	[107]	Solution	Solar energy	MF	Method	2010	Conference	IEEE
90	[108]	Solution	Solar energy	MF	Method	2010	Journal	SD
91	[109]	Solution	Solar energy	MB	Method	2009	Conference	Springer
92	[110]	Validation	Solar energy	MF	Tool	2009	Conference	IEEE
93	[111]	Solution	Solar energy	MF	Method	2009	Conference	Other
94	[112]	Solution	Solar energy	MF	Method	2009	Conference	IEEE
95	[113]	Evaluation	Solar energy	MF	Tool	2009	Journal	IEEE
96	[114]	Validation	Solar energy	MB	Tool	2008	Conference	ACM
97	[115]	Solution	Solar energy	MF	Tool	2007	Journal	ACM
98	[116]	Evaluation	Solar energy	MF	Tool	2007	Conference	ACM

4. Results

This section aims to comprehensively depict the research landscape regarding EHWS energy prediction through the results from the SMS. By conducting a thorough exploration and analysis of these inquiries, this chapter offers a comprehensive overview of the current state of EHWS energy-prediction research. It serves as a foundation and reference for the subsequent discussions and conclusions in the following sections.

4.1. RQ1: What Types of Research Have Been Conducted in this Research Field over a Period of Time and How Has It Developed?

After classifying the selected papers according to their research types, their respective proportions were plotted in Figure 3. The solution proposal-type papers had the highest proportion, accounting for 55% of all research types, followed by validation research, which accounted for 26% of all papers. Evaluation research constituted 15% of all papers, and only 4% of the papers belonged to experience papers. To date, this study has not identified any opinion papers or philosophical papers. The distribution of research types reveals that, in the EHWS field, researchers have primarily focused on proposing new methods or improving existing ones, providing valuable insights and directions for future research.

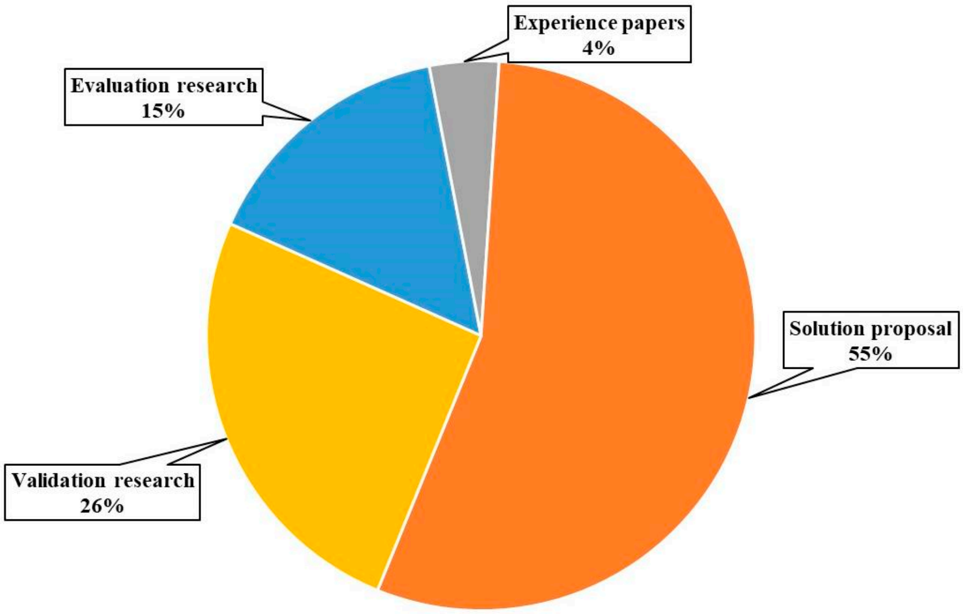


Figure 3. Classification of research types.

In this study, Figure 4 was drawn according to the production method of the bubble chart in [15]. Figure 4 shows the publication trends of different research types across different years. It is evident from the figure that, except for the years 2008, 2011, and 2014, the solution proposal papers consistently dominate among all types of papers, reaching their peak between 2016 and 2019. This indicates that proposing new methods or improving existing ones is a major concern for more researchers in the EHWS field, and it provides more ideas and research directions for future researchers. Validation research and evaluation research experienced occasional interruptions in 2017, but the research in these areas did not stop, indicating that some researchers are still inclined toward validation and evaluation papers. Only four experience papers were published between 2007 and 2022, indicating that no authoritative recommendations have been proposed in this field. During this study period, no opinion papers or philosophical papers were identified. In the future, the EHWS energy-prediction field will require more researchers to put forward viewpoints and suggestions.

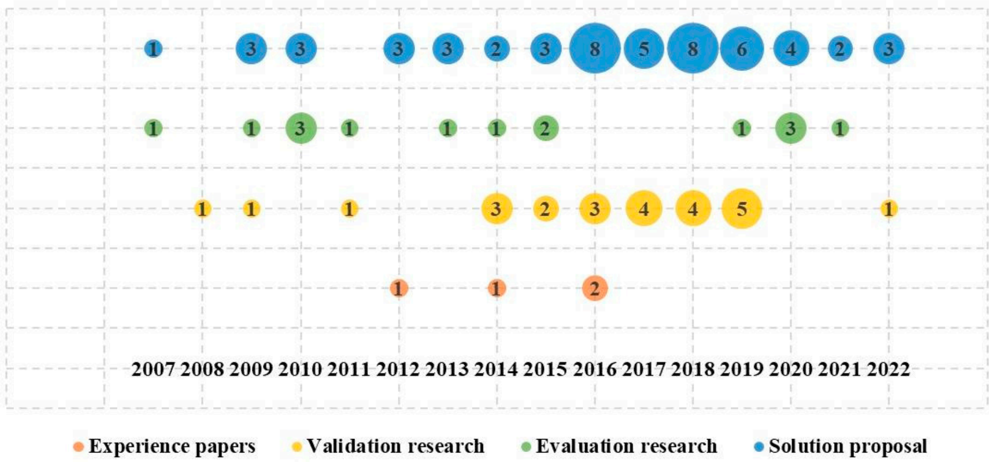


Figure 4. Publishing by research type by year.

4.2. RQ2:What Are the Predicted Energy Types?

EHWS energy prediction can be classified into five categories: solar energy, heat energy, wind energy, vibration energy, and radio frequency. As shown in Figure 5, 86% of the papers predicted solar energy as the energy type. This is because solar energy has better periodicity and predictability when compared to other types of energy, and most researchers are more concerned with the harvesting and prediction of solar energy. The second most common energy type is solar or wind energy, accounting for 8% of the total, indicating that the methods selected by researchers apply to both solar and wind energy and have better adaptability. The third most common energy type is wind energy, accounting for 3%. The abrupt changes in wind energy can cause significant errors regarding energy prediction. Radio frequency and vibration energy account for 2% and 1%, respectively. In the screened literature, no researchers were found to harvest and predict heat energy.

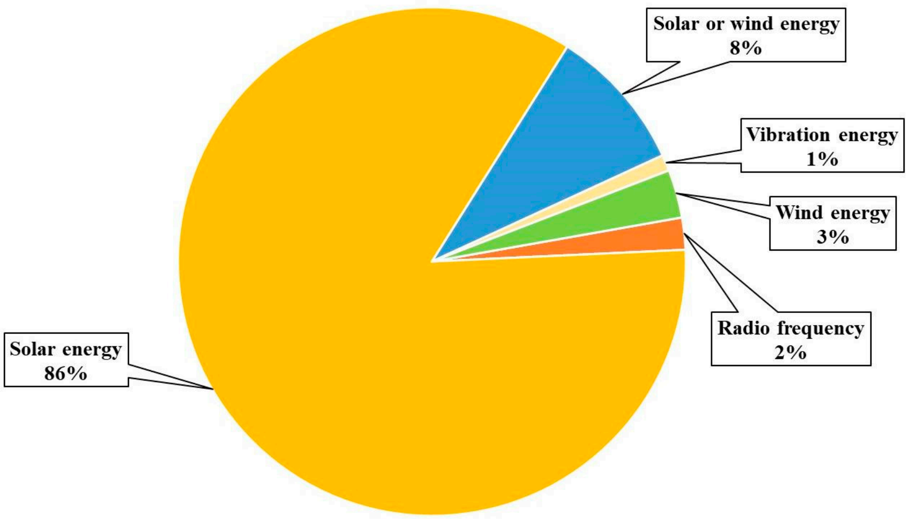


Figure 5. Types of energy harvested.

4.3. RQ3:What Prediction Methods Are Used?

Categorizing the prediction methods into three categories: model-free prediction, model-based prediction, and machine learning. As shown in Figure 6, of the 98 articles screened, 44 articles covered model-free prediction, accounting for 45% of the total, 29 articles covered model-based prediction, accounting for 30% of the total, and 25 articles covered machine learning, accounting for 25% of the total.

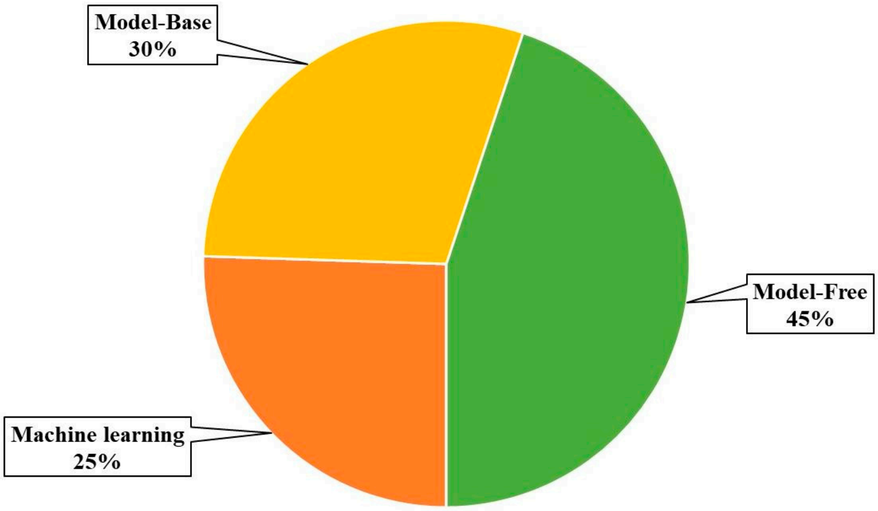


Figure 6. Prediction method.

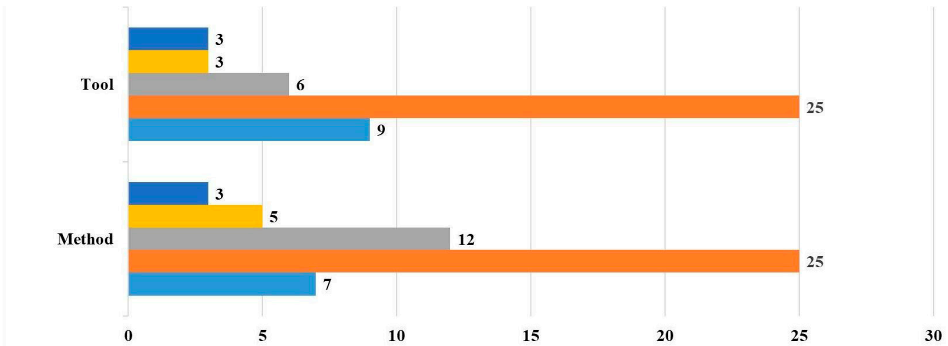
Based on the selected articles, this study analyzed the research trends in the field of EHWS. As shown in Figure 7, the number of publications gradually increased from 2011 to 2016. Among the years we selected, the publication rate in 2008 was the lowest with only one article, while in 2016, the publication rate was the highest, reaching 13 articles. The research hotspot in this field was between 2016 and 2019, with about 10 papers published each year. From 2019, the number of publications decreased annually, but there was a resurgence in 2022. Overall, this study believes that there is still high research significance in the field of EHWS, and researchers can further explore this area.

Figure 7. Papers by publication year.

4.4. RQ4: How Many Tool Papers and Method Papers Were Screened Out?

According to the screened literature, a total of 98 research papers related to energy prediction for EHWS were published between 2007 and 2022. Among them, 53 (53% of the total) were methodological papers, and 47 (47% of the total) were tool papers.

Figure 8 displays the number of tool and methodology-based papers published by different publishing units. From the chart, it can be observed that the number of tool papers and methodology-based papers published in Springer and IEEE is the same. The number of tool papers published in ACM is greater than the number of methodology-based papers. For the remaining publishing units, the number of methodology-based papers is fewer than the number of tool papers. Among the selected 52 methodology-based papers, the main objectives of these methods were twofold: (1) to propose new methods to provide more referenceable prediction methods for the current research field, and (2) to improve the existing methods to enhance prediction accuracy or reduce complexity.



	Method	Tool
Springer	3	3
ScienceDirect	5	3
Other	12	6
IEEE	25	25
ACM	7	9

Figure 8. Tools and method papers published by different publishers.

After organizing all the tool papers, this study found that the energy-prediction methods used by researchers as tools also varied in their objectives. For example, a long-term energy-saving task-scheduling method was designed using reinforcement learning and energy-prediction technology, greatly improving energy utilization efficiency and enhancing the long-term service quality of wireless sensor nodes [40]. In addition, an energy management scheme was implemented based on the energy values derived from the prediction method [51]. This method can set the threshold rate of energy consumption to ensure sufficient energy supply for wireless sensor operation, even during periods without energy supply. These tools have provided useful technical support for researchers to address different application scenarios and needs.

In this study, the distribution of tool or technique papers across different prediction methods in the field of energy prediction is illustrated in Figure 9. The figure also reveals the relative attention given to different methods in the energy-prediction domain, providing insights for future research and innovation.

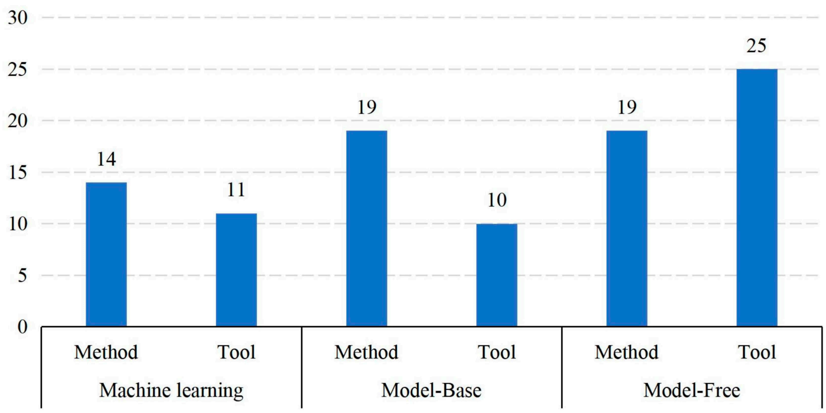


Figure 9. Tools or methods papers for different prediction methods.

Firstly, it can be observed that the highest number of tool papers belongs to the model-free prediction method, reaching a total of 25 articles. Secondly, for the method papers, both the model-free and model-based prediction methods have 19 articles each. This indicates that the model-free and model-based prediction methods have received similar attention in terms of technique papers. These different methods may apply to various application scenarios and levels of problem complexity. The number of papers on machine learning prediction methods is the lowest, with only 14 articles. This can be attributed to the particularity of the energy-prediction field and the requirements for data and models, which may result in the relatively limited application of machine learning methods.

4.5. RQ5: How Are Relevant Research Papers Distributed?

According to the publication types, this study classified the selected papers into two categories: international journals and international conferences. By classifying the 98 pieces of relevant literature into different types, this study found that 51% of the paper types were conference proceedings and 49% were journal publications. Additionally, this paper analyzed the publisher labels and publication types and plotted a chart, as shown in Figure 10. It can be seen that the number of conference papers published by IEEE and ACM is significantly higher than that of journal papers, while the number of conference papers published by other publishers is significantly lower than that of journal papers. It is worth noting that the authors' preference for journal publications and conference proceedings is similar, indicating that the number of journal platforms and conference platforms in this field is similar, with relatively balanced academic exchange opportunities.

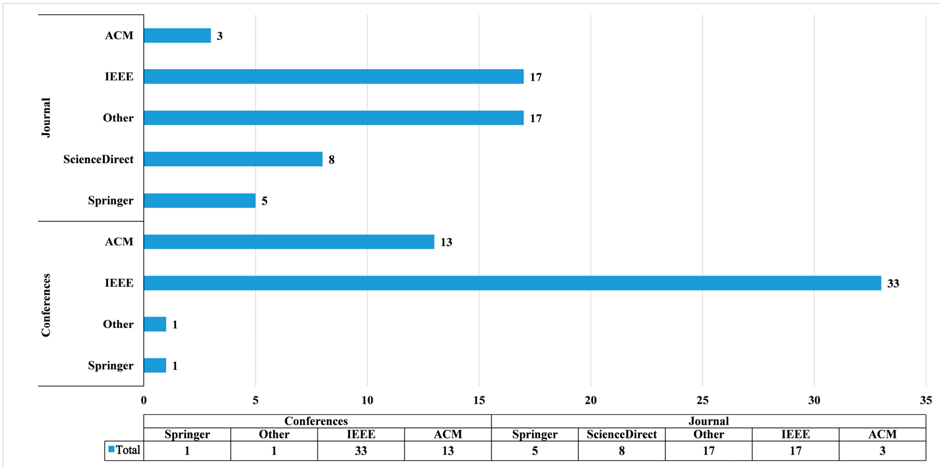


Figure 10. Publisher statistics by publishing type.

Figure 11 depicts the distribution of publishers in the selected 98 papers; it can be found that among these publishers, IEEE had the largest share, accounting for 51% of the total. Other types of publishers accounted for 19% of the total, followed by ACM with 16% of the papers published under this outlet. ScienceDirect and Springer accounted for 8% and 6% of the total, respectively. It can be observed from the figure that IEEE is the most preferred publisher in the field of energy prediction regarding EHWS.

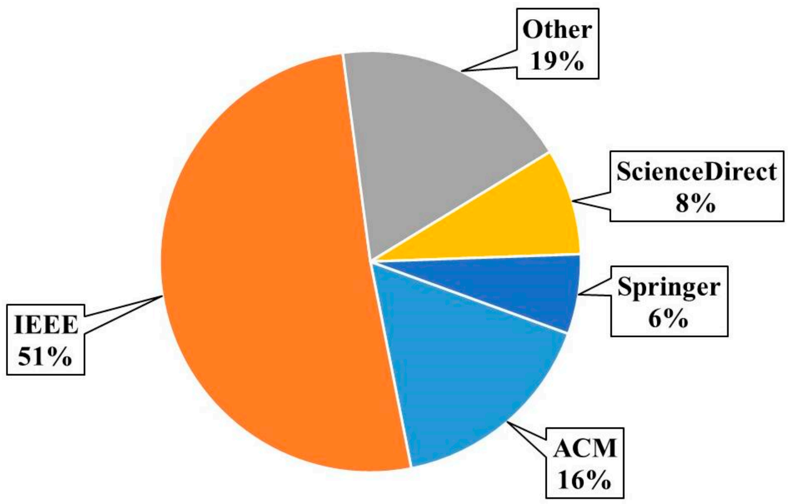


Figure 11. Proportion of paper publishers.

5. Discussion of Prediction Methods

This section aims to analyze the current research status in the field of EHWS energy prediction. Based on the classification of non-model prediction, model-based prediction, and machine learning prediction, a detailed analysis of the proposed prediction methods in the selected literature was conducted. For each type of method, the technical approaches employed, improvements made, and limitations are discussed, followed by a brief evaluation and analysis.

5.1. Model-Free Prediction Methods

In energy-constrained wireless sensor networks, EHWS non-model energy-prediction methods are widely used to avoid wasting resources due to node shutdowns caused by insufficient resources. After analyzing the selected literature, this study found that the development and improvement of non-model prediction algorithms are mainly centered around three basic methods: exponentially weighted moving average (EWMA), weather-conditioned moving average (WCMA), and Pro-Energy.

5.1.1. EWMA and Its Related Methods

Kansal et al. [115] first applied EWMA to energy-prediction methods in 2007. This method assumes that the available energy in a given time slot of the day is similar to the energy harvested in the same time slot in the previous few days. The energy harvested in the same time slot in the previous few days is weighted and averaged, and an appropriate weighting factor is assigned through a decay factor. The predicted energy value is obtained by combining the harvested energy of the day with the weighted average. However, this method produces serious prediction errors when weather conditions frequently change. To improve the prediction performance, Hassan et al. [99] proposed solar energy prediction based on the additive decomposition (SEPAD) method, which considers three factors that affect energy generation: daily cycles, seasonal effects, and daily energy trends. SEPAD uses three EWMA filters to calculate these three factors, respectively, and then combines them to obtain the desired predicted energy value. They collected one week of real energy data and compared SEPAD with three other algorithms on this data set, and the results show that SEPAD using this method accurately considers the impact of other factors and effectively improves prediction performance. Yang et al. [94] combined long-term seasonal and short-term daily energy situations and proposed the weather-conditioned exponential weighted moving average (WC-EWMA) method based on EWMA. This method considers weather fluctuations and proposes a parameter that represents the cloudiness threshold. When the weather fluctuation value is less than the cloudiness threshold, WC-EWMA does not consider the impact of that day on the predicted value, thereby improving the accuracy of the prediction.

As a classic non-model prediction method that is applied to EHWS, although EWMA has the advantages of low complexity and low computation, it cannot predict energy very accurately and produces significant errors when weather conditions change frequently. Therefore, it is rarely used in systems that require high prediction accuracy. SEPAD and WC-EWMA, which were improved based on EWMA from different perspectives, have significantly improved prediction accuracy while only increasing by a small amount of complexity, providing choices for researchers who need higher prediction accuracy.

5.1.2. WCMA and Its Related Methods

In 2009, Piorno et al. [112] proposed a method called WCMA. This method introduced a parameter called the GAP based on EWMA. The GAP represents the change in weather conditions compared to previous days. which measures the relationship between the solar conditions of the day and those of the previous days, taking into account the past solar values and the average solar energy available in the previous days. By scaling and weighing the energy average of the same time slots of the previous days using the GAP, the prediction accuracy of the method can be improved. When weather conditions frequently change, the average prediction error of WCMA is reduced by nearly 20% compared to EWMA. Bergonzini et al. [108] improved WCMA and proposed a method called weather-conditioned moving average-phase displacement regulator (WCMA-PDR). This method stores the difference between a value related to each time slot in a day and the corresponding predicted value in memory while assigning weights in an exponentially weighted moving manner. Although this method introduces additional parameters and increases the memory and computational requirements, it can eliminate or greatly reduce prediction errors. Experimental results show that the average error of the WCMA-PDR algorithm is 9.2%, and it has better performance than WCMA. Ren et al. [50] combined real weather forecast information with the WCMA method and proposed an efficient and reliable prediction algorithm called real-forecast weather moving average (RWMA). This method adjusts the prediction results of the next time slot based on the error between the harvested energy and the predicted energy of the previous time slots. RWMA considers the influence of real forecast weather on solar energy acquisition and analyzes the association between historical solar energy data and meteorological types. It numerically analyzes the effect of real forecast weather on solar energy harvesting and applies it to the prediction algorithm. Such analysis helps to predict solar energy acquisition more accurately. Secondly, RWMA introduces a proportional adjustment mechanism. In addition to considering the historical weather data horizontally, the RWMA algorithm also considers the previous data vertically to account for the associativity between consecutive time slots. Dehwah et al. [61] proposed a dynamic version of the weather-conditioned moving average technique called universal dynamic-WCMA (UD-WCMA) for predicting the variation in energy harvesting in EHWS. Compared with the previous prediction methods, the UD-WCMA algorithm introduces a dynamic model and adaptively adjusts the weight factors according to the weather changes. This method combines the actual energy information harvested in the past time slots with a set of stored configuration file energy information to predict future energy and designs an adaptive weighting factor that is dependent on weather changes. Therefore, UD-WCMA is more flexible than the existing uncalibrated prediction methods. Experimental validation on real solar irradiance data shows that the UD-WCMA algorithm performs well in prediction performance and maintains a sufficiently low complexity to be implemented on low-power wireless sensor nodes.

As another typical model-free prediction method, WCMA introduces a critical GAP factor and considers the impact of frequent changes in weather conditions, which reduces the prediction error but still does not satisfy researchers. Therefore, the WCMA-PDR and RWMA methods focus on improving the prediction accuracy of WCMA by error correction. UD-WCMA processes the average energy by using a set of stored configuration files to achieve satisfactory prediction performance.

5.1.3. Pro-Energy and Its Related Methods

Cammarano et al. [98] proposed a novel energy-prediction method for a multi-source energy-harvesting sensor network named Pro-Energy, which is different from traditional methods. This method maintains a pool of "typical configuration files" that store past energy observation data for several days. When predicting energy, it first finds the configuration file that is most similar to today's weather from the pool and combines it with the previously harvested real energy data. This method significantly outperforms previous methods in short- and medium-term energy prediction, improving the prediction accuracy by 60%. However, when Pro-Energy does not have a stored configuration file for specific weather conditions, it exhibits serious bias. Subsequently, Cammarano et al. [71] proposed Pro-Energy-VLT in 2016, which extends Pro-Energy by combining energy prediction with time slots of variable lengths to adapt to the dynamic variability of energy. In Pro-Energy-VLT, a weight is first assigned to each time slot according to the change in the energy-harvesting process. Then, the size and distribution of time slots are readjusted according to the weight and the size of time slots. Finally, the energy-harvesting data stored in the Pro-Energy-VLT pool is updated according to the new time slot setting. By running this slot-adaptation process periodically, Pro-Energy-VLT generates new time slot Settings based on dynamic energy changes. The experimental results show that Pro-Energy-VLT further improves prediction accuracy while reducing memory usage and resource consumption during energy prediction. Muhammad et al. [60] improved Pro-Energy to create IPro-Energy, which uses weighted-file (WP) technology to predict energy by processing the two most similar configuration files. The core modules of IPro-Energy include analyzer, predictor, and updater. The analyzer module selects the most similar energy-harvesting configuration to the current day based on the minimum mean absolute error (MAE). The predictor module predicts energy harvesting in the short and medium term based on the most similar configurations. The updater module refreezes the entries in the energy-harvesting configuration pool at the end of each day. These improvements allow IPro-Energy to perform better in terms of energy prediction accuracy, execution time, and throughput. Through experimental comparison, IPro-Energy achieves satisfactory performance in short-, medium-, and long-term prediction. Deb et al. [25] combined past and current harvested energy information to improve Pro-Energy and proposed a new energy-prediction algorithm, Enhanced-Pro, which uses the correlation coefficient to select matching configuration files and selects a tuning algorithm to check the difference between the selected file and the specific situation of the day. Finally, the prediction equation is used to obtain the prediction result. The experimental results showed that this method can achieve a lower prediction error than Pro-Energy.

Pro-Energy is the most complex among the three model-free prediction methods, with higher prediction accuracy, but it also has the disadvantage of being heavily dependent on the stored configuration files. To address this issue, researchers have optimized the existing methods in terms of variable time slots, configuration files, and tuning algorithms, resulting in significant improvements. Pro-Energy-VLT improves prediction accuracy and reduces resource consumption by introducing the concept of variable time slots. IPro-Energy processes configuration files using weighted-file technology and achieves satisfactory performance, according to researchers. Enhanced-Pro introduces correlation coefficients in selecting matching configuration files and uses a tuning algorithm to check the differences between the selected file and the specific situation of the day, resulting in a lower prediction error than Pro-Energy. These improvement methods provide useful insights for solving the energy-prediction problem in multi-source energy-harvesting sensor networks and provide important references for future research.

5.2. Model-Based Predicting Methods

Model-based energy-prediction methods are currently the most widely used approach for energy prediction. This class of methods models energy information and predicts future energy by combining past harvested energy information with other relevant information. It takes into account various factors that affect energy more comprehensively, resulting in more accurate predictions of future energy conditions.

5.2.1. Weather-Based Prediction Models

Sharma et al. [86] analyzed global solar irradiance and cloud cover predictions and proposed a model. They used a polynomial model to calculate the relationship between time and solar power during the day, transforming weather forecasts into solar or wind energy-harvesting energy predictions and improving prediction accuracy. The prediction accuracy of the proposed method is higher on moderate time scales, that is, hours to days. To verify the effectiveness of this prediction method, this paper designs three different types of energy-harvesting system experiments. In each case, the performance of the prediction model based on the weather forecast and the prediction model based on the past are compared. The experimental results show that the prediction model based on weather prediction performs significantly better in terms of the related performance indicators of the system. Herrería-Alonso et al. [28] calculated the solar altitude at different times of the day and modeled the energy that can be harvested corresponding to the given time slots based on the solar altitude. The model does not require local energy-harvesting information in the past few days or any specific adjustments for each different scene or location. It only needs to perform some low-complexity operations to provide accurate predictions for any prediction range. BASHA et al. [84] proposed a distributed solar energy-prediction algorithm that utilizes surrounding spatial information and predicts future solar energy based on multivariate linear regression and local climate conditions. In contrast to previous prediction methods, the core component of this distributed solar forecasting model is the distributed pseudo-inverse algorithm. This article is the first to propose and develop a distributed version of sensor networks. Experimental results show that their model improves the prediction accuracy by 20% relative to previous models that use environmental data or spatial data. Edalat et al. [75] proposed a low-cost solar energy-prediction algorithm based on the WCMA model, applying autoregressive time series models at the start of each day to further improve the model using the moving average of harvested energy in the past few days. A prediction method called the autoregressive-WCMA (AR-WCMA). AR-WCMA combines the advantages of AR time series models and WCMA to better schedule and forecast actual weather conditions. Simulation experiments verify the energy-prediction accuracy of the AR-WCMA method under real weather conditions. Janković et al. [57] proposed a solar energy-prediction model based on a two-level weather forecast, which uses information on weather forecasts every hour for the next 24 h to predict the amount of energy that can be harvested within the same time interval. This value is used as the initial prediction, and the final prediction for the next time slot is obtained by comparing the difference between the energy harvested in the previous time slot and the predicted energy. Furthermore, the model optimizes energy utilization to achieve ENO and adjusts energy storage and usage strategies based on weather forecasts. However, the model currently focuses primarily on short-term future predictions and requires further enhancements for predictions beyond 24 h. To improve the model, efforts can be made to better integrate weather forecasts and historical data, combining multiple predictions to reduce error rates. Subsequently, Janković et al. [26] enhanced solar energy-prediction accuracy by combining weather prediction data, fuzzy logic filtering, and clear-sky radiation modeling. The distinguishing features of this prediction model include obtaining maximum solar radiation information using a clear-sky radiation model, predicting cloud cover and precipitation probability using weather forecast data, adjusting predictions based on humidity and atmospheric pressure prediction errors through a fuzzy logic filter, and correcting solar energy predictions based on previous time period energy-prediction errors.

5.2.2. Innovative Approaches

Ahmed et al. [58] proposed a solar and wind dual-source prediction model based on a sampling theory. The model defines three predictors using sampling operators after operations such as sampling, generating kernels, and approximating error estimation. It allows adjustable kernel sizes that are compatible with EHWS and utilizes dynamic weighting factors. Unlike previous models, this model does not result in a decrease in prediction accuracy for different prediction ranges. The prediction model is suitable for various prediction ranges and can achieve good prediction results in different prediction ranges. However, further research and improvements are still required to enhance its prediction accuracy and applicability. Subsequently, Ahmed et al. [45] considered that energy distribution has different smoothness and changes, and different sampling operator kernels are needed for different types of configuration files. They proposed an adaptive LINE-P model that calculates adaptive weighted parameters based on stored-energy curves independent of fixed length time slots and fixed weight parameters. In addition, they also proposed a configuration-file-compression method that can reduce memory requirements by 50% while achieving 90% accuracy. Koirala et al. [36] proposed a multi-node energy-prediction method for the harvesting of RF energy using neighboring nodes' energy-harvesting information to predict future energy availability. They also developed a mathematical model to calculate the optimal value of the prediction interval, which can effectively improve prediction accuracy. However, the literature does not provide an accurate estimation method for determining the optimal prediction interval, which is crucial for developing prediction-based energy management systems. Zhang et al. [47] considered the practical situation and proposed an energy prediction algorithm based on the IEA platform. They modeled physical information such as voltage, resistance, and capacitance and combined these parameter information operations to obtain the energy that can be harvested in future time slots. Through experimental testing, the accuracy of energy prediction can be higher when the IEA node performs data transmission. Kosunalp [62] proposed a new wind energy-prediction method (WEP), which differs from existing methods by only considering the current wind energy generation situation rather than the energy generation situation of the previous day. In comparative experiments, WEP provides more accurate prediction results under conditions of frequent fluctuations and can provide more accurate prediction results in a shorter time for situations with low wind speeds.

For model-based energy-prediction methods, it is important to combine other information to improve the accuracy of the predictions. For example, Herrería-Alonso et al. [28] combined information on solar altitude to predict a given time slot, while the authors of [55,57,84] combined weather forecast information to make predictions. These models can provide accurate energy predictions by considering factors such as the climate and the weather forecasts of the surrounding environment, as well as the node's energy-harvesting capabilities, to better meet the needs of different scenarios.

5.3. Machine Learning

To improve the accuracy of solar energy-prediction algorithms, many researchers have considered combining machine learning techniques with prediction methods.

5.3.1. Neural Networks

Neural networks possess the capability to handle complex non-linear relationships, thereby providing more accurate prediction outcomes. Their adaptability and generalization ability, achieved through learning the patterns and trends within data, make them well-suited for energy-harvesting prediction in diverse environments and conditions. They excel in effectively processing energy-harvesting systems that involve a substantial number of data points, ultimately enhancing the accuracy and reliability of the predictions. Consequently, neural networks have been widely applied to energy prediction within EHWS.

Li et al. [30] proposed a prediction model for solar energy harvesting based on the long short-term memory (LSTM) network. The model architecture consists of an input layer, a hidden layer (employing the LSTM layer), and an output layer (composed of fully connected and regression layers). The LSTM layer within the hidden layer is capable of handling long-term dependencies in time series data by utilizing memory cells and control gates for the selective forgetting and retention of historical data, thus facilitating solar energy-harvesting prediction. Dhillon et al. [31] proposed a solar energy-prediction model based on the characteristics of feedforward neural networks with low memory requirements. The model predicts energy 24 h in advance based on temperature, pressure, relative humidity, dew point, wind speed, zenith angle, and harvested historical values. Compared with other methods, the proposed model uses the independent component analysis (ICA) algorithm for feature extraction, which can better extract the relevant features in the input data. At the same time, reference signal generation is introduced to improve the accuracy of prediction. The experimental results show that the proposed model achieves high accuracy in the prediction of solar irradiance and surpasses other traditional prediction methods. Yang et al. [41] applied the LSTM network to energy-prediction problems and selected mean squared error (MSE) as the loss function while using Adam optimization as the optimizer to achieve an accurate estimation of the total energy for sensor nodes in a cycle. Although this prediction method increases some of the computational complexity, it can greatly enhance the stability of the sensor network in areas with variable weather conditions. Compared with previous forecasting methods, this LSTM network-based method is better able to deal with the randomness and seasonal changes in energy forecasting. Experimental results show that compared with traditional methods, the energy prediction method based on the LSTM network can improve energy utilization efficiency while maintaining a low estimation error. Al-Omary et al. [42] combined an artificial neural network (ANN) with an energy-harvesting wireless sensor network to predict the harvestable energy in the future. Using ANN can obtain more accurate results than traditional algorithms and achieve higher accuracy when weather conditions change dramatically. This algorithm effectively improves the accuracy of short-term prediction while reducing complexity. Ge et al. [44] proposed a solar energy-prediction model based on the LSTM and empirical mode decomposition (EMD) methods. The EMD method decomposes time-series data into a series of relatively stable component sequences, and the LSTM network is trained with similar solar energy profiles in the database, which can reduce prediction errors. Li et al. [73] selected a solar energy-prediction model based on neural networks as the method for estimating the energy that can be harvested by an estimation node in the short-term prediction range. The neural network used supervised learning with the error backpropagation (BP) algorithm for training, which can learn the regularity of energy production from historical data and achieve the prediction of future energy production.

Utilizing neural networks for prediction in EHWS offers advantages in terms of adaptability, generalization ability, and handling large-scale datasets. However, neural networks also possess drawbacks such as high data requirements, complex parameter tuning, and limited interpretability. To enhance prediction performance, the following approaches can be considered: (1) data augmentation and ensemble techniques to improve the generalization and prediction accuracy of neural networks by increasing the sample size, introducing new features, or employing data-integration methods; (2) the optimization of network architecture by exploring different structures and topologies, such as deep networks and attention mechanisms, to enhance the performance and learning capabilities of neural networks; (3) automated parameter tuning by utilizing algorithms for hyperparameter optimization and automatic parameter tuning to search for optimal configurations, thereby improving prediction performance; and (4) improvements in interpretability by integrating other models or methods with higher interpretability, such as decision trees and rule extraction, to enhance the interpretation and understanding of the prediction results.

5.3.2. Other Techniques

In addition to neural networks, some machine-learning techniques have also been used in solar energy prediction. These techniques include decision trees, support vector machines, random forests, and k-nearest neighbor algorithms, among others. Each technique possesses its unique strengths and suitable scenarios.

Nengroo et al. [22] employed the kernel recursive least squares (KRLS), a prediction model, to address distributed renewable energy-prediction problems. The KRLS model, based on the recursive least squares method with a kernel function, exhibits remarkable performance in regression problems and finds extensive application in smart grid scenarios. This model utilizes a smaller non-static vocabulary to handle regression problems, resulting in better predictive outcomes when compared to other machine learning models. Sharma et al. [43] employed machine-learning ensemble methods and constructed an energy-prediction model using the R interface. This method combines multiple machine-learning algorithms and predicts the working cycles of nodes by predicting solar radiation. In the ensemble prediction, they trained multiple individual prediction models and combined them. The simulation results demonstrate that this approach accurately predicts solar irradiance without being affected by seasonal variations and other meteorological parameters. Sharma et al. [55] investigated the applicability of five machine-learning models for modeling solar-irradiance prediction by considering seasonal effects and evaluating their performance using the statistical metric and the correlation coefficient. By using historical solar intensity observations as a training dataset, solar radiation prediction over different prediction time horizons is achieved without the limitation of seasonal variations and the availability of input parameters. These methods are then validated by evaluating performance metrics such as prediction accuracy, correlation coefficient, and root mean square error. Kraemer et al. [64] constructed an energy-prediction model based on k-nearest neighbors and utilized easily accessible numerical weather forecast data for effective energy budget planning, which is crucial for resource-constrained nodes. However, this model relies on weather forecast data, which inherently contain uncertainty, potentially introducing errors into the predictions. Azmat et al. [77] used two machine-learning techniques, linear regression (LR) and decision tree (DT), to model the harvested energy based on real-time power measurements in the wireless radio spectrum and proved that the prediction accuracy using LR was higher than DT. By using the LR model and DT model to predict RF energy in wireless-powered communication, compared with the single model prediction method, the accuracy and reliability of prediction are improved. Kosunalp [72] proposed QL-SEP, a solar energy-prediction algorithm based on Q-learning, in 2016. Q-learning is a reinforcement learning method that predicts future actions based on past observations. Combining this method with an EWMA resulted in QL-SEP, which considers not only observations from the past few days but also the current weather conditions, achieving higher prediction accuracy. However, the QL-SEP algorithm also suffers from certain drawbacks, such as larger prediction errors in low solar intensity scenarios. Finally, some researchers have also proposed methods to improve traditional prediction algorithms. Ma et al. [27] considered the problem of large prediction errors regarding the standard least mean squares (LMS) prediction algorithm when weather changes fluctuate. They proposed the correlated least mean squares prediction algorithm by combining weather change factors with the LMS algorithm, which effectively improved the accuracy of short-term prediction while reducing complexity. Ghuman et al. [83] proposed a model for predicting solar irradiance called ASIM, which is based on an increasing Markov chain. The model determines the state dependence of the basic Markov chain and proposes a mechanism to reduce the complexity of the Markov chain, making it more practical in wireless sensor networks. The ASIM model takes into account the state dependencies of solar radiation patterns and determines these dependencies by a comprehensive evaluation of solar radiation datasets from around the globe. The experimental results show that the ASIM model can predict solar radiation patterns more and more accurately as the order of the Markov chain increases.

Based on machine learning, prediction methods have certain hardware requirements and may require the sacrifice of some energy for complex data calculations and model updates. However, in some critical scenarios that require a long-term stable operation, the predictive accuracy of this method can efficiently meet the needs. Judging from the number of articles on energy prediction based on machine learning in recent years, this study believes that this method has significant development potential in the future.

6. Current Challenges and Future Research Directions

This chapter focuses on the research directions and challenges in the field of energy prediction for EHWS. The current challenges are discussed and elaborated in detail in Section 6.1. In light of the current developments in the EHWS energy prediction, this study presents two challenges and provides a brief overview of each challenge. Section 6.2 presents the future research outlook, identifying three feasible research directions and providing a concise overview and analysis of each direction.

6.1. Current Challenges

EHWS are typically equipped with one or more energy-harvesting units to harvest energy and use energy-storage units (batteries or capacitors) to store energy for use during energy shortages. What makes EHWS unique is that its energy source is infinite, and the harvested energy is dynamic and uncertain. Therefore, EHWS needs to adaptively adjust the working state of their sensors based on the dynamic nature of the harvested energy to ensure that the nodes do not interrupt their operations due to insufficient energy while meeting service requirements. Based on the literature reviewed, we believe that the following challenges exist for energy prediction in EHWS:

Challenge 1: How to avoid energy waste and energy shortages according to ENO.

During the energy budget process, when the ENO performance is high, it is appropriate to moderately increase the energy allocation for node energy consumption to improve sensor performance and avoid energy waste. When the ENO performance is low, it is appropriate to moderately decrease the energy allocation for node energy consumption to store more energy in the battery and avoid energy waste. Therefore, understanding how to integrate the ENO trend into the energy budget and dynamically capture ENO performance becomes the core issue of energy budgeting.

Challenge 2: How to balance accuracy and complexity in practical applications.

For EHWS, using low-complexity prediction methods can reduce energy waste, which is critical for maintaining the long-term operation of the sensor nodes. However, low-complexity prediction methods may come with lower accuracy, which can cause sensor nodes to use energy in an unreasonable way, leading to unnecessary energy waste. Therefore, understanding how to balance complexity and accuracy in practical applications is a key issue.

Challenge 3: The impact of diverse external environmental factors on energy prediction.

During the energy-prediction process, the efficiency of the energy-harvesting system is directly influenced by external environmental factors. The uncertainty associated with these factors introduces deviations in energy prediction, thereby affecting the accuracy of energy prediction [117]. Moreover, the external environment itself is characterized by inherent uncertainty, which can further increase prediction errors and compromise the accuracy of energy management and planning. Therefore, addressing the challenge of mitigating the impact of diverse external environmental factors on energy prediction becomes crucial for enhancing prediction precision and reliability.

Challenge 4: The dynamic nature of energy consumption poses challenges for energy management.

The efficient management of EHWS relies on a comprehensive understanding of energy harvesting and consumption. The rate of energy consumption may vary across different tasks and operational states [118]. Changes in transmission, computation, and sensing tasks, as well as variations in the operational modes of the nodes (e.g., sleep, work, and wake-up), all influence energy consumption. Accurately simulating and predicting the dynamic nature of energy consumption, as well as maintaining a balance between consumption and harvesting, presents a challenging problem.

Challenge 5: Addressing inaccuracies in predictions resulting from sudden environmental variability.

Currently, energy forecasting methods in EHWS face challenges when confronted with sudden changes in the surrounding environment. These abrupt environmental changes may include sudden shifts in climate conditions, electromagnetic interference, the instability of network topology, and movement or damage to sensor nodes, among other factors. These changes can lead to momentary fluctuations in energy, which traditional energy forecasting methods often struggle to capture and adapt to in such unpredictable circumstances [50]. Hence, improving energy forecasting methods to enhance adaptability to abrupt environmental changes is a critical task. Addressing this challenge requires in-depth research into the mechanisms by which environmental changes impact energy consumption. It also entails the development of more flexible and adaptive prediction algorithms to ensure that sensor networks can reliably operate and transmit data in unstable environmental conditions.

Challenge 6: Significant decrease in accuracy of energy forecasting methods for long-term predictions.

Long-term predictions present significant challenges within the existing forecasting methods. Current prediction methods predominantly focus on short and medium-term timeframes, making long-term forecasting challenging due to various factors. Firstly, the accuracy of long-term predictions is influenced by multiple factors, including data reliability, model complexity, and algorithm selection, which can result in biases and errors in prediction outcomes [95]. Secondly, long-term forecasting necessitates considering data and trends over longer time spans and accounting for more unknown variables and uncertainty factors, which may increase data volume and computational complexity. Some sensor nodes may struggle to handle large-scale data and complex calculations, limiting their applicability in long-term forecasting [107]. Furthermore, sustaining model accuracy over extended time spans is crucial for long-term forecasting, but model performance may degrade with time, leading to instability in long-term predictions [60]. Therefore, developing reliable long-term forecasting methods is a significant challenge in current forecasting research, requiring a comprehensive consideration of factors such as data, models, and computational resources to make progress.

6.2. Future Research Directions

As a key technology, EHWS has attracted extensive attention. However, there are still some challenges and limitations in the current research, including the lack of optimal management schemes, complex energy-harvesting environments, and dynamic energy-consumption patterns. Therefore, to promote the further development of energy-prediction methods for EHWS, this review aims to comprehensively sort out and analyze the existing research results and propose future research directions.

Research direction 1: Energy management methods based on energy prediction.

Regardless of whether it is a model-free energy-prediction method, a model-based energy-prediction method, or a machine learning-based energy prediction method, predicting the availability of future energy is important to prolong the lifespan of wireless sensor nodes and improve node duty cycles and throughput [119]. Currently, energy management lacks consideration of the trend of ENO changes, which may cause varying degrees of energy waste or energy shortages. Therefore, an important research direction is understanding how to track the trend of ENO changes in energy-management methods to avoid energy waste and shortages and improve ENO performance.

Research direction 2: Adaptive adjustment of duty cycle based on predicted energy.

The effective adjustment of the duty cycle of wireless sensor nodes can be achieved by accurately predicting future energy availability and the energy level in the battery. The duty cycle adjustment method should consider the matching ability between energy harvesting and consumption, and the reward function should mainly consider the duty cycle as a factor [120]. However, the current methods lack consideration of ENO performance, which may lead to a decrease in the performance of the node. Therefore, a key issue regarding adaptive duty cycle adjustment in EHWS is how to dynamically match energy harvesting and consumption during the energy-harvesting process and how to integrate ENO reward factors into the duty cycle reward function to improve ENO performance.

Research direction 3: Adaptive adjustment of charging and discharging current based on the remaining energy budget.

Battery charging and discharging control methods affect not only the energy storage efficiency of batteries but also their lifespan [121]. Inefficient energy storage in the battery will result in energy waste, and the arbitrary use of battery charging and discharging current will lead to overcharging and over-discharging. By accurately judging the energy shortage status of the wireless sensor network based on the remaining energy budget of the sensor node, the adaptive adjustment of charging and discharging current can be achieved and the dynamic adjustment of the remaining energy budget and the neutral threshold of battery energy can be made. The development of charging and discharging strategies should consider the impact of energy harvesting on battery lifespan in dynamic environments. Improving the learning ability of the adaptive energy management strategy regarding battery performance in response to dynamic changes in energy harvesting is an important issue that needs to be addressed to prolong battery lifespan.

Research Direction 4: Energy-aware scheduling strategies based on energy prediction.

Energy-aware scheduling by intelligently managing energy resources enhances network reliability, stability, and performance, thereby addressing complex environmental conditions and node variations. Energy-prediction methods assist nodes in evaluating their energy consumption patterns. By predicting energy consumption, nodes can allocate tasks and resources effectively, thereby avoiding energy depletion and imbalances, leading to improved energy management and network performance. Hence, energy prediction plays a pivotal role in enhancing energy-aware scheduling strategies, and optimizing energy-aware scheduling based on known energy levels represents a crucial challenge.

Research Direction 5: Addressing environmental variability in energy forecasting methods.

Dealing with environmental variability is a critical challenge in energy-harvesting wireless sensor networks. This variability can encompass changes in weather conditions, temperature fluctuations, alterations in light conditions, and more. To enhance system reliability, it is essential to investigate how energy forecasting methods can adapt to these environmental changes. Firstly, environmental sensing and monitoring are key; this involves the use of various sensors to continuously monitor environmental parameters such as temperature, illumination, and wind speed in real time. Subsequently, adaptive algorithm design becomes necessary to ensure that energy-prediction models can automatically adjust their parameters in response to environmental changes, thereby adapting to new circumstances. Incorporating factors of change into algorithm design can also help improve prediction accuracy, as demonstrated in [50], which applied numerical analysis of weather forecasts' impact on solar energy harvesting to prediction algorithms.

Research Direction 6: Ensuring the accuracy of long-term energy forecasting methods.

Accurate long-term energy forecasting is crucial for ensuring system sustainability. This form of forecasting goes beyond the short and medium term, predicting energy supply over extended time periods. This direction includes time series analysis, which can be used to identify the effects of seasonality, periodicity, and trends, thereby improving future predictions. Additionally, data mining and trend analysis techniques are highly valuable for identifying and leveraging past energy consumption patterns to formulate more precise forecasts. Ultimately, long-term forecasting can be used to develop sustainable energy management strategies, including energy storage and distribution, to ensure the long-term stability of the system. This is paramount for achieving system sustainability and stability.

7. Conclusions

This study employed the SMS method to conduct a screening analysis of energy-prediction methods for EHWS between 2007 and 2022. The SMS method, being a widely adopted literature review approach, was applied to the field of EHWS energy prediction. In line with the rigorous SMS process employed in other domains, researchers ensured the reliability and accuracy of the review.

Based on a comprehensive examination of the research landscape, this study identified current challenges and proposed future research directions, offering valuable guidance to scholars in the field. Within the context of existing energy-prediction optimization methods, this paper highlights the importance of striking a balance between low complexity and high accuracy, as well as addressing the impact of external environmental factors on energy prediction. To better guide future research, it is suggested that integrating energy prediction with energy management is necessary. However, existing energy management approaches primarily focus on singular objectives, such as node lifespan or duty cycle. In future studies, greater attention should be given to optimizing multiple objectives simultaneously in energy-management strategies, including factors such as energy efficiency, node lifespan, and communication quality. Furthermore, it is worth exploring the development of adaptive and flexible energy management algorithms that account for the uncertainty of energy prediction and the dynamic nature of the system.

Author Contributions: Study conception and design, Z.Y. and Y.G.; data collection, Z.Y.; analysis and interpretation of results, Z.Y., J.W. and S.Y.; draft manuscript preparation, Z.Y., R.L. and X.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Grant number 62162052, 62262052, 62306157), in part by the Natural Science Foundation of Ningxia Province (Grant number 2021AAC03041, 2022AAC03004, 2020AAC03280), and in part by the Key R & D projects of Ningxia Province (Grant number 2021BEB04016, 2022BDE03007).

Data Availability Statement: The literature cited in this study can be found at: https://libraries.acm.org (accessed on 1 March 2023), https://www.webofscience.com (accessed on 7 March 2023), https://ieeexplore.ieee.org (accessed on 7 March 2023).

Acknowledgments: We extend our sincere gratitude to all the individuals who provided valuable insights and support throughout the research process. Their contributions have been instrumental in shaping this paper.

Conflicts of Interest: The authors declare that they have no conflict of interest to report regarding the present study.

References

1. Roy, S.; Azad, A.W.; Baidya, S.; Alam, M.K.; Khan, F. Powering solutions for biomedical sensors and implants inside the human body: A comprehensive review on energy harvesting units, energy storage, and wireless power transfer techniques. *IEEE Trans. Power Electron.* **2022**, *37*, 12237–12263. [CrossRef]
2. Ouni, R.; Saleem, K. Framework for sustainable wireless sensor network based environmental monitoring. *Sustainability* **2022**, *14*, 8356. [CrossRef]
3. Pragadeswaran, S.; Madhumitha, S.; Gopinath, S. Certain investigation on military applications of wireless sensor network. *Int. J. Adv. Res. Sci. Commun. Technol.* **2021**, *3*, 14–19. [CrossRef]
4. Sharma, V.; Mukherji, U.; Joseph, V.; Gupta, S. Optimal energy management policies for energy harvesting sensor nodes. *IEEE Trans. Wirel. Commun.* **2010**, *94*, 1326–1336. [CrossRef]
5. Faheem, M.; Umar, M.; Butt, R.A.; Raza, B.; Ngadi, M.A.; Gungor, V.C. Software defined communication framework for smart grid to meet energy demands in smart cities. In Proceedings of the 2019 7th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 25–26 April 2019; pp. 51–55.
6. Popovic, G.; Djukanovic, G.; Kanellopoulos, D. Cluster head relocation based on selfish herd hypothesis for prolonging the life span of wireless sensor networks. *Electronics* **2018**, *7*, 403. [CrossRef]
7. Faheem, M.; Ashraf, M.W.; Butt, R.A.; Raza, B.; Ngadi, M.A.; Gungor, V.C. Ambient energy harvesting for low powered wireless sensor network based smart grid applications. In Proceedings of the 2019 7th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 25–26 April 2019; pp. 26–30.
8. Paul, J.; Barari, M. Meta-analysis and traditional systematic literature reviews—What, why, when, where, and how? *Psychol. Mark.* **2022**, *39*, 1099–1115. [CrossRef]
9. Zhao, L.; Alhoshan, W.; Ferrari, A.; Letsholo, K.J.; Ajagbe, M.A.; Chioasca, E.V.; Batista-Navarro, R.T. Natural language processing for requirements engineering: A systematic mapping study. *ACM Comput. Surv. (CSUR)* **2021**, *54*, 1–41. [CrossRef]
10. Linnenluecke, M.K.; Marrone, M.; Singh, A.K. Conducting systematic literature reviews and bibliometric analyses. *Aust. J. Manag.* **2020**, *45*, 175–194. [CrossRef]
11. Nguyen, M.; Nguyen, C.; Tran, H.; Nguyen, H. Energy harvesting for devices in wireless sensor networks: A Review. *EAI Endorsed Trans. Internet Things* **2023**, *9*, e2. [CrossRef]
12. Alamu, O.; Olwal, T.O.; Djouani, K. Energy Harvesting Techniques for Sustainable Underwater Wireless Communication Networks: A Review. *e-Prime-Adv. Electr. Eng. Electron. Energy* **2023**, *5*, 100265. [CrossRef]
13. Hezekiah, J.D.K.; Ramya, K.C.; Radhakrishnan, S.B.K.; Kumarasamy, V.M.; Devendran, M.; Ramalingam, A.; Maheswar, R. Review of Next-Generation Wireless Devices with Self-Energy Harvesting for Sustainability Improvement. *Energies* **2023**, *16*, 5174. [CrossRef]
14. Sharma, A.; Kakkar, A. A review on solar forecasting and power management approaches for energy-harvesting wireless sensor networks. *Int. J. Commun. Syst.* **2020**, *33*, e4366. [CrossRef]
15. Petersen, K.; Feldt, R.; Mujtaba, S.; Mattsson, M. Systematic mapping studies in software engineering. In Proceedings of the 12th International Conference on Evaluation and Assessment in Software Engineering, Bari, Italy, 26–27 June 2008; Volume 12, pp. 1–10.
16. Wohlin, C. Guidelines for snowballing in systematic literature studies and a replication in software engineering. In Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering, London, UK, 13–14 May 2014; pp. 1–10.
17. Petersen, K.; Vakkalanka, S.; Kuzniarz, L. Guidelines for conducting systematic mapping studies in software engineering: An update. *Inf. Softw. Technol.* **2015**, *64*, 1–18. [CrossRef]

18. Wieringa, R.; Maiden, N.; Mead, N.; Rolland, C. Requirements engineering paper classification and evaluation criteria: A proposal and a discussion. *Requir. Eng.* **2006**, *11*, 102–107. [CrossRef]
19. Sah, D.K.; Hazra, A.; Kumar, R.; Amgoth, T. Harvested Energy Prediction Technique for Solar-Powered Wireless Sensor Networks. *IEEE Sens. J.* **2022**, *23*, 8932–8940. [CrossRef]
20. Yallappa, K.P.; Naik, A.A. An Enhanced Routing Protocol for Energy Harvesting-Wireless Sensor Networks for Optimal Execution of IoT Applications. In Proceedings of the 2022 IEEE 7th International Conference for Convergence in Technology (I2CT), Mumbai, India, 7–9 April 2022; pp. 1–9.
21. Azzam, M.; Bouida, Z.; Ibnkahla, M. Irradiance and Temperature Forecasting for Energy Harvesting Units in IoT Sensors using SARIMA-KF. In Proceedings of the 2022 IEEE Wireless Communications and Networking Conference (WCNC), Austin, TX, USA, 10–13 April 2022; pp. 1701–1706.
22. Nengroo, S.H.; Jin, H.; Lee, S. Management of distributed renewable energy resources with the help of a wireless sensor network. *Appl. Sci.* **2022**, *12*, 6908. [CrossRef]
23. Kim, D.; Ahn, J.; Shin, J.; Cha, H. Ray tracing-based light energy prediction for indoor batteryless sensors. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2021**, *5*, 1–27. [CrossRef]
24. Al-Omary, M.; Aljarrah, R.; Albatayneh, A.; Jaradat, M. A composite moving average algorithm for predicting energy in solar powered wireless sensor nodes. In Proceedings of the 2021 18th International Multi-Conference on Systems, Signals & Devices (SSD), Monastir, Tunisia, 22–25 March 2021; pp. 1047–1052.
25. Deb, M.; Roy, S. Enhanced-pro: A new enhanced solar energy harvested prediction model for wireless sensor networks. *Wirel. Pers. Commun.* **2021**, *117*, 1103–1121. [CrossRef]
26. Jankovic, S.; Saranovac, L. Prediction of harvested energy for wireless sensor node. *Elektron. Elektrotechnika* **2020**, *26*, 23–31. [CrossRef]
27. Ma, D.; Zhang, C.; Ma, L. A C-LMS prediction algorithm for rechargeable sensor networks. *IEEE Access* **2020**, *8*, 69997–70004. [CrossRef]
28. Herrería-Alonso, S.; Suárez-González, A.; Rodríguez-Pérez, M.; Rodríguez-Rubio, R.F.; López-García, C. A solar altitude angle model for efficient solar energy predictions. *Sensors* **2020**, *20*, 1391. [CrossRef] [PubMed]
29. Mouapi, A.; Hakem, N.; Kandil, N. Piezoelectric energy harvesting prediction and efficient management for industrial wireless sensor. *Appl. Sci.* **2020**, *10*, 8486. [CrossRef]
30. Li, Y.; He, X.; Yin, C. Energy aware opportunistic routing for energy harvesting wireless sensor networks. In Proceedings of the 2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications, London, UK, 31 August–3 September 2020; pp. 1–6.
31. Dhillon, S.; Madhu, C.; Kaur, D.; Singh, S. A solar energy forecast model using neural networks: Application for prediction of power for wireless sensor networks in precision agriculture. *Wirel. Pers. Commun.* **2020**, *112*, 2741–2760. [CrossRef]
32. Dhillon, S.K.; Madhu, C.; Kaur, D.; Singh, S. A review on precision agriculture using wireless sensor networks incorporating energy forecast techniques. *Wirel. Pers. Commun.* **2020**, *113*, 2569–2585. [CrossRef]
33. Ashraf, N.; Faizan, M.; Asif, W.; Qureshi, H.K.; Iqbal, A.; Lestas, M. Energy management in harvesting enabled sensing nodes: Prediction and control. *J. Netw. Comput. Appl.* **2019**, *132*, 104–117. [CrossRef]
34. Ahmed, F.; Kervadec, C.; Le Moullec, Y.; Tamberg, G.; Annus, P. Autonomous wireless sensor networks: Implementation of transient computing and energy prediction for improved node performance and link quality. *Comput. J.* **2019**, *62*, 820–837. [CrossRef]
35. Cui, X.; Ma, D.; Ma, L. An EH-WSN Clustering Algorithm Based on Energy Prediction. In Proceedings of the 2019 IEEE 11th International Conference on Communication Software and Networks (ICCSN), Chongqing, China, 12–15 June 2019; pp. 509–513.
36. Koirala, B.; Dahal, K.; Keir, P.; Chen, W. A multi-node energy prediction approach combined with optimum prediction interval for RF powered WSNs. *Sensors* **2019**, *19*, 5551. [CrossRef]
37. Li, Y.; Si, J.; Ma, S.; Hu, X. Using energy-aware scheduling weather forecast based harvesting for reconfigurable hardware. *IEEE Trans. Sustain. Comput.* **2018**, *4*, 109–117. [CrossRef]
38. Bao, X.; Han, L.; He, X.; Tan, W.; Fan, T. Optimizing maximum monitoring frequency and guaranteeing target coverage and connectivity in energy harvesting wireless sensor networks. *Mob. Inf. Syst.* **2019**, *2019*, 6312589. [CrossRef]
39. Ikeda, N.; Shigeta, R.; Kawahara, Y. Energy prediction for energy management method of sensor node powered by temperature difference between air and shallow underground soil. In Proceedings of the 2019 IEEE SENSORS, Montreal, QC, Canada, 27–30 October 2019; pp. 1–4.
40. Xu, Y.; Lee, H.G.; Tan, Y.; Wu, Y.; Chen, X.; Liang, L.; Qiao, L.; Liu, D. Tumbler: Energy efficient task scheduling for dual-channel solar-powered sensor nodes. In Proceedings of the 56th Annual Design Automation Conference 2019, Las Vegas, NV, USA, 2–6 June 2019; pp. 1–6.
41. Yang, M.; Yang, L.; Zhu, Z.; Wang, H.; Qian, H. Data Censoring in Renewable Energy Enabled Wireless Sensor Networks. In Proceedings of the 2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall), Honolulu, HI, USA, 22–25 September 2019; pp. 1–5.
42. Al-Omary, M.; Hassini, K.; Fakhfakh, A.; Kanoun, O. Prediction of energy in solar powered wireless sensors using artificial neural network. In Proceedings of the 2019 16th International Multi-Conference on Systems, Signals & Devices (SSD), Istanbul, Turkey, 21–24 March 2019; pp. 288–293.

43. Sharma, A.; Kakkar, A. Machine learning based optimal renewable energy allocation in sustained wireless sensor networks. *Wirel. Netw.* **2019**, *25*, 3953–3981. [CrossRef]
44. Ge, Y.; Nan, Y.; Bai, L. A hybrid prediction model for solar radiation based on long short-term memory, empirical mode decomposition, and solar profiles for energy harvesting wireless sensor networks. *Energies* **2019**, *12*, 4762. [CrossRef]
45. Ahmed, F.; Tamberg, G.; Le Moullec, Y.; Annus, P. Adaptive LINE-P: An adaptive linear energy prediction model for wireless sensor network nodes. *Sensors* **2018**, *18*, 1105. [CrossRef] [PubMed]
46. Li, X.; Xie, N. Multi-Model Fusion Harvested Energy Prediction Method for Energy Harvesting WSN Node. In Proceedings of the 2018 IEEE International Conference on Electron Devices and Solid State Circuits (EDSSC), Shenzhen, China, 6–8 June 2018; pp. 1–2.
47. Zhang, Y.; Gao, H.; Cheng, S.; Li, J. An efficient EH-WSN energy management mechanism. *Tsinghua Sci. Technol.* **2018**, *23*, 406–418. [CrossRef]
48. Wu, Y.; Li, B.; Zhang, F. Predictive power management for wind powered wireless sensor node. *Future Internet* **2018**, *10*, 85. [CrossRef]
49. Munir, D.; Shah, S.T.; Mughal, D.M.; Park, K.H.; Chung, M.Y. Duty cycle optimizing for wifi-based iot networks with energy harvesting. In Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication, Langkawi, Malaysia, 5–7 January 2018; pp. 1–6.
50. Ren, H.; Guo, J.; Sun, L.; Han, C. Prediction algorithm based on weather forecast for energy-harvesting wireless sensor networks. In Proceedings of the 2018 17th IEEE International Conference on Trust, Security and Privacy in Computing and Communications/12th IEEE International Conference on Big Data Science and Engineering (TrustCom/BigDataSE), New York, NY, USA, 1–3 August 2018; pp. 1785–1790.
51. Amjad, M.; Qureshi, H.K.; Lestas, M.; Mumtaz, S.; Rodrigues, J.J. Energy prediction based MAC layer optimization for harvesting enabled WSNs in smart cities. In Proceedings of the 2018 IEEE 87th Vehicular Technology Conference (VTC Spring), Porto, Portugal, 3–6 June 2018; pp. 1–6.
52. Draskovic, S.; Ahmed, R.; Lin, C.; Thiele, L. A case for atmospheric transmittance: Solar energy prediction in wireless sensor nodes. In Proceedings of the 2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), Halifax, NS, Canada, 30 July–3 August 2018; pp. 427–434.
53. Bouguera, T.; Diouris, J.F.; Andrieux, G.; Chaillout, J.J.; Jaouadi, R. A novel solar energy predictor for communicating sensors. *IET Commun.* **2018**, *12*, 2145–2149. [CrossRef]
54. Manjili, Y.S.; Vega, R.; Jamshidi, M.M. Data-analytic-based adaptive solar energy forecasting framework. *IEEE Syst. J.* **2017**, *12*, 285–296. [CrossRef]
55. Sharma, A.; Kakkar, A. Forecasting daily global solar irradiance generation using machine learning. *Renew. Sustain. Energy Rev.* **2018**, *82*, 2254–2269. [CrossRef]
56. Ashraf, N.; Christofides, N.; Lestas, M. Combined data rate and energy management in wireless sensor networks with energy harvesting capability. In Proceedings of the 2018 IEEE Conference on Decision and Control (CDC), Miami, FL, USA, 17–19 December 2018; pp. 6717–6722.
57. Janković, S.; Saranovac, L. Improving energy usage in energy harvesting wireless sensor nodes using weather forecast. In Proceedings of the 2017 25th Telecommunication Forum (TELFOR), Belgrade, Serbia, 21–22 November 2017; pp. 1–4.
58. Ahmed, F.; Tamberg, G.; Le Moullec, Y.; Annus, P. Dual-source linear energy prediction (LINE-P) model in the context of WSNs. *Sensors* **2017**, *17*, 1666. [CrossRef]
59. Rodway, J.; Musilek, P. Harvesting-aware energy management for environmental monitoring WSN. *Energies* **2017**, *10*, 607. [CrossRef]
60. Muhammad; Qureshi, H.K.; Saleem, U.; Saleem, M.; Pitsillides, A.; Lestas, M. Harvested energy prediction schemes for wireless sensor networks: Performance evaluation and enhancements. *Wirel. Commun. Mob. Comput.* **2017**, *2017*, 6928325. [CrossRef]
61. Dehwah, A.H.; Elmetennani, S.; Claudel, C. UD-WCMA: An energy estimation and forecast scheme for solar powered wireless sensor networks. *J. Netw. Comput. Appl.* **2017**, *90*, 17–25. [CrossRef]
62. Kosunalp, S. An energy prediction algorithm for wind-powered wireless sensor networks with energy harvesting. *Energy* **2017**, *139*, 1275–1280. [CrossRef]
63. Basagni, S.; Di Valerio, V.; Koutsandria, G.; Petrioli, C.; Spenza, D. WHARP: A wake-up radio and harvesting-based forwarding strategy for green wireless networks. In Proceedings of the 2017 IEEE 14th International Conference on Mobile Ad Hoc and Sensor Systems (MASS), Orlando, FL, USA, 22–25 October 2017; pp. 257–265.
64. Kraemer, F.A.; Ammar, D.; Braten, A.E.; Tamkittikhun, N.; Palma, D. Solar energy prediction for constrained IoT nodes based on public weather forecasts. In Proceedings of the Seventh International Conference on the Internet of Things, Linz, Austria, 22–25 October 2017; pp. 1–8.
65. Ashraf, N.; Asif, W.; Qureshi, H.K.; Lestas, M. Active energy management for harvesting enabled wireless sensor networks. In Proceedings of the 2017 13th Annual Conference on Wireless On-demand Network Systems and Services (WONS), Jackson, WY, USA, 21–24 February 2017; pp. 57–60.
66. Zou, T.; Lin, S.; Feng, Q.; Chen, Y. Energy-efficient control with harvesting predictions for solar-powered wireless sensor networks. *Sensors* **2016**, *16*, 53. [CrossRef] [PubMed]

67. Ahmed, F.; Le Moullec, Y.; Annus, P. FYPSim: An estimation framework for energy harvesting and energy prediction for WSNs. In Proceedings of the 2016 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW), Nantou, Taiwan, 27–29 May 2016; pp. 1–2.
68. Kosunalp, S. A performance evaluation of solar energy prediction approaches for energy-harvesting wireless sensor networks. *Int. J. Appl. Math. Electron. Comput.* **2016**, *4*, 424–427.
69. Jushi, A.; Pegatoquet, A.; Le, T.N. Wind energy harvesting for autonomous wireless sensor networks. In Proceedings of the 2016 Euromicro Conference on Digital System Design (DSD), Limassol, Cyprus, 31 August–2 September 2016; pp. 301–308.
70. Rout, R.R.; Krishna, M.S.; Gupta, S. Markov decision process-based switching algorithm for sustainable rechargeable wireless sensor networks. *IEEE Sens. J.* **2016**, *16*, 2788–2797. [CrossRef]
71. Cammarano, A.; Petrioli, C.; Spenza, D. Online energy harvesting prediction in environmentally powered wireless sensor networks. *IEEE Sens. J.* **2016**, *16*, 6793–6804. [CrossRef]
72. Kosunalp, S. A new energy prediction algorithm for energy-harvesting wireless sensor networks with Q-learning. *IEEE Access* **2016**, *4*, 5755–5763. [CrossRef]
73. Li, J.; Liu, D. An energy aware distributed clustering routing protocol for energy harvesting wireless sensor networks. In Proceedings of the 2016 IEEE/CIC International Conference on Communications in China (ICCC), Chengdu, China, 27–29 July 2016; pp. 1–6.
74. Xu, J.; Yoo, S.; Heiser, J.; Kalb, P. Sensor network based solar forecasting using a local vector autoregressive ridge framework. In Proceedings of the 31st Annual ACM Symposium on Applied Computing, Pisa, Italy, 4–8 April 2016; pp. 2113–2118.
75. Edalat, N.; Motani, M. Energy-aware task allocation for energy harvesting sensor networks. *EURASIP J. Wirel. Commun. Netw.* **2016**, *2016*, 1–14. [CrossRef]
76. Rodway, J.; Krömer, P.; Karimi, S.; Musilek, P. Differential evolution optimized fuzzy controller for wireless sensor network energy management. In Proceedings of the 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Vancouver, BC, Canada, 24–29 July 2016; pp. 352–358.
77. Azmat, F.; Chen, Y.; Stocks, N. Predictive modelling of RF energy for wireless powered communications. *IEEE Commun. Lett.* **2015**, *20*, 173–176. [CrossRef]
78. Shin, M.; Joe, I. Energy management algorithm for solar-powered energy harvesting wireless sensor node for internet of things. *IET Commun.* **2016**, *10*, 1508–1521. [CrossRef]
79. Kwon, K.; Yang, J.; Yoo, Y. Adaptive control of the packet transmission period with solar energy harvesting prediction in wireless sensor networks. *Sensors* **2015**, *15*, 9741–9755. [CrossRef] [PubMed]
80. Ren, X.; Liang, W.; Xu, W. Quality-aware target coverage in energy harvesting sensor networks. *IEEE Trans. Emerg. Top. Comput.* **2014**, *3*, 8–21. [CrossRef]
81. Aoudia, F.A.; Gautier, M.; Berder, O. GRAPMAN: Gradual power manager for consistent throughput of energy harvesting wireless sensor nodes. In Proceedings of the 2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Hong Kong, China, 30 August–2 September 2015; pp. 954–959.
82. Shahriar, M.S.; Rahman, M.S. Urban sensing and smart home energy optimisations: A machine learning approach. In Proceedings of the 2015 International Workshop on Internet of Things Towards Applications, Seoul, Korea, 1 November 2015; pp. 19–22.
83. Ghuman, M.F.; Iqbal, A.; Qureshi, H.K.; Lestas, M. Asim: Solar energy availability model for wireless sensor networks. In Proceedings of the 3rd International Workshop on Energy Harvesting & Energy Neutral Sensing Systems, Seoul, Republic of Korea, 1 November 2015; pp. 21–26.
84. Basha, E.; Jurdak, R.; Rus, D. In-network distributed solar current prediction. *ACM Trans. Sens. Netw. (TOSN)* **2014**, *11*, 1–28. [CrossRef]
85. Renner, C.; Nguyen, P.A.T. A system for efficient dissemination of weather forecasts for sustainable solar-powered sensors. In Proceedings of the 2015 Sustainable Internet and ICT for Sustainability (SustainIT), Madrid, Spain, 14–15 April 2015; pp. 1–8.
86. Sharma, N.; Gummeson, J.; Irwin, D.; Zhu, T.; Shenoy, P. Leveraging weather forecasts in renewable energy systems. *Sustain. Comput. Inform. Syst.* **2014**, *4*, 160–171. [CrossRef]
87. Li, Y.; Jia, Z.; Li, X. Task scheduling based on weather forecast in energy harvesting sensor systems. *IEEE Sens. J.* **2014**, *14*, 3763–3765. [CrossRef]
88. Martinez, G.; Li, S.; Zhou, C. Wastage-aware routing in energy-harvesting wireless sensor networks. *IEEE Sens. J.* **2014**, *14*, 2967–2974. [CrossRef]
89. Buchli, B.; Sutton, F.; Beutel, J.; Thiele, L. Dynamic power management for long-term energy neutral operation of solar energy harvesting systems. In Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems, Memphis, TN, USA, 3–6 November 2014; pp. 31–45.
90. Tapparello, C.; Ayatollahi, H.; Heinzelman, W. Energy harvesting framework for network simulator 3 (ns-3). In Proceedings of the 2nd International Workshop on Energy Neutral Sensing Systems, Memphis, TN, USA, 6 November 2014; pp. 37–42.
91. Basu, C.; Caubel, J.J.; Kim, K.; Cheng, E.; Dhinakaran, A.; Agogino, A.M.; Martin, R.A. Sensor-based predictive modeling for smart lighting in grid-integrated buildings. *IEEE Sens. J.* **2014**, *14*, 4216–4229. [CrossRef]
92. Achleitner, S.; Kamthe, A.; Liu, T.; Cerpa, A.E. SIPS: Solar irradiance prediction system. In Proceedings of the IPSN-14 13th International Symposium on Information Processing in Sensor Networks, Berlin, Germany, 15–17 April 2014; pp. 225–236.

93. Le, T.N.; Sentieys, O.; Berder, O.; Pegatoquet, A.; Belleudy, C. Adaptive filter for energy predictor in energy harvesting wireless sensor networks. In Proceedings of the 26th International Conference on Architecture of Computing Systems 2013, Prague, Czech Republic, 19–22 February 2013; pp. 1–4.
94. Yang, S.; Yang, X.; McCann, J.A.; Zhang, T.; Liu, G.; Liu, Z. Distributed networking in autonomic solar powered wireless sensor networks. *IEEE J. Sel. Areas Commun.* **2013**, *31*, 750–761. [CrossRef]
95. Renner, C. Solar harvest prediction supported by cloud cover forecasts. In Proceedings of the 1st International Workshop on Energy Neutral Sensing Systems, Rome, Italy, 13 November 2013; pp. 1–6.
96. Kim, M.; Kyung, C.M.; Yi, K. An energy management scheme for solar-powered Wireless Visual Sensor Networks toward uninterrupted operations. In Proceedings of the 2013 International SoC Design Conference (ISOCC), Busan, Korea, 17–19 November 2013; pp. 23–26.
97. Lu, J.; Whitehouse, K. SunCast: Fine-grained prediction of natural sunlight levels for improved daylight harvesting. In Proceedings of the 11th International Conference on Information Processing in Sensor Networks, Beijing, China, 16–20 April 2012; pp. 245–256.
98. Cammarano, A.; Petrioli, C.; Spenza, D. Pro-Energy: A novel energy prediction model for solar and wind energy-harvesting wireless sensor networks. In Proceedings of the 2012 IEEE 9th International Conference on Mobile Ad-Hoc and Sensor Systems (MASS 2012), Las Vegas, NV, USA, 8–11 October 2012; pp. 75–83.
99. Hassan, M.; Bermak, A. Solar harvested energy prediction algorithm for wireless sensors. In Proceedings of the 2012 4th Asia Symposium on Quality Electronic Design (ASQED), Penang, Malaysia, 10–11 July 2012; pp. 178–181.
100. Dang, N.; Bozorgzadeh, E.; Venkatasubramanian, N. Quares: A quality-aware renewable energy-driven sensing framework. *Sustain. Comput. Inform. Syst.* **2012**, *2*, 171–183. [CrossRef]
101. Dondi, D.; Zappi, P.; Rosing, T.Š. A scheduling algorithm for consistent monitoring results with solar powered high-performance wireless embedded systems. In Proceedings of the IEEE/ACM International Symposium on Low Power Electronics and Design, Fukuoka, Japan, 1–3 August 2011; pp. 259–264.
102. Noh, D.K.; Kang, K. Balanced energy allocation scheme for a solar-powered sensor system and its effects on network-wide performance. *J. Comput. Syst. Sci.* **2011**, *77*, 917–932. [CrossRef]
103. Sharma, N.; Gummeson, J.; Irwin, D.; Shenoy, P. Cloudy computing: Leveraging weather forecasts in energy harvesting sensor systems. In Proceedings of the 2010 7th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), Boston, MA, USA, 21–25 June 2010; pp. 1–9.
104. Piorno, J.R.; Bergonzini, C.; Atienza, D.; Rosing, T.S. HOLLOWS: A power-aware task scheduler for energy harvesting sensor nodes. *J. Intell. Mater. Syst. Struct.* **2010**, *21*, 1317–1335. [CrossRef]
105. Prabhakar, T.V.; Devasenapathy, S.; Jamadagni, H.; Prasad, R.V. Smart applications for energy harvested WSNs. In Proceedings of the 2010 Second International Conference on Communication Systems and Networks (COMSNETS 2010), Bangalore, India, 5–9 January 2010; pp. 1–7.
106. Ali, M.I.; Al-Hashimi, B.M.; Recas, J.; Atienza, D. Evaluation and design exploration of solar harvested-energy prediction algorithm. In Proceedings of the 2010 Design, Automation & Test in Europe Conference & Exhibition (DATE 2010), Dresden, Germany, 8–12 March 2010; pp. 142–147.
107. Jiang, Z.; Jin, X.; Zhang, Y. A weather-condition prediction algorithm for solar-powered wireless sensor nodes. In Proceedings of the 2010 6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM), Chengdu, China, 23–25 September 2010; pp. 1–4.
108. Bergonzini, C.; Brunelli, D.; Benini, L. Comparison of energy intake prediction algorithms for systems powered by photovoltaic harvesters. *Microelectron. J.* **2010**, *41*, 766–777. [CrossRef]
109. Noh, D.K.; Wang, L.; Yang, Y.; Le, H.K.; Abdelzaher, T. Minimum variance energy allocation for a solar-powered sensor system. In Proceedings of the Distributed Computing in Sensor Systems: 5th IEEE International Conference, DCOSS 2009, Marina del Rey, CA, USA, 8–10 June 2009; Springer: Berlin/Heidelberg, Germany, 2009; pp. 44–57.
110. Bergonzini, C.; Brunelli, D.; Benini, L. Algorithms for harvested energy prediction in batteryless wireless sensor networks. In Proceedings of the 2009 3rd International Workshop on Advances in Sensors and Interfaces, Trani, Italy, 25–26 June 2009; pp. 144–149.
111. Bergonzini, C.; Lee, B.; Piorno, J.R.; Rosing, T.S. Management of solar harvested energy in actuation-based and event-triggered systems. In Proceedings of the Energy Harvesting Workshop, Blacksburg, VA, USA, 28–29 January 2009.
112. Piorno, J.R.; Bergonzini, C.; Atienza, D.; Rosing, T.S. Prediction and management in energy harvested wireless sensor nodes. In Proceedings of the 2009 1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace & Electronic Systems Technology, Aalborg, Denmark, 17–20 May 2009; pp. 6–10.
113. Moser, C.; Thiele, L.; Brunelli, D.; Benini, L. Adaptive power management for environmentally powered systems. *IEEE Trans. Comput.* **2009**, *59*, 478–491. [CrossRef]
114. Moser, C.; Thiele, L.; Brunelli, D.; Benini, L. Robust and low complexity rate control for solar powered sensors. In Proceedings of the Conference on Design, Automation and Test in Europe, Munich, Germany, 10–14 March 2008; pp. 230–235.
115. Kansal, A.; Hsu, J.; Zahedi, S.; Srivastava, M.B. Power management in energy harvesting sensor networks. *ACM Trans. Embed. Comput. Syst. (TECS)* **2007**, *6*, 32-es. [CrossRef]

116. Sorber, J.; Kostadinov, A.; Garber, M.; Brennan, M.; Corner, M.D.; Berger, E.D. Eon: A language and runtime system for perpetual systems. In Proceedings of the 5th International Conference on Embedded Networked Sensor Systems, Sydney, Australia, 6–9 November 2007; pp. 161–174.
117. VanDeventer, W.; Jamei, E.; Thirunavukkarasu, G.S.; Seyedmahmoudian, M.; Soon, T.K.; Horan, B.; Mekhilef, S.; Stojcevski, A. Short-term PV power forecasting using hybrid GASVM technique. *Renew. Energy* **2019**, *140*, 367–379. [CrossRef]
118. Sandhu, M.M.; Khalifa, S.; Jurdak, R.; Portmann, M. Task scheduling for energy-harvesting-based IoT: A survey and critical analysis. *IEEE Internet Things J.* **2021**, *8*, 13825–13848. [CrossRef]
119. Hong, T.; Pinson, P.; Wang, Y.; Weron, R.; Yang, D.; Zareipour, H. Energy forecasting: A review and outlook. *IEEE Open Access J. Power Energy* **2020**, *7*, 376–388. [CrossRef]
120. Li, Y.; Wang, R.; Yang, Z. Optimal scheduling of isolated microgrids using automated reinforcement learning-based multi-period forecasting. *IEEE Trans. Sustain. Energy* **2021**, *13*, 159–169. [CrossRef]
121. Haram, M.H.S.M.; Lee, J.W.; Ramasamy, G.; Ngu, E.E.; Thiagarajah, S.P.; Lee, Y.H. Feasibility of utilising second life EV batteries: Applications, lifespan, economics, environmental impact, assessment, and challenges. *Alex. Eng. J.* **2021**, *60*, 4517–4536. [CrossRef]