Wireless Communications and Mobile Computing

# Artificial Intelligence of Things (AIoT) Systems

Lead Guest Editor: Dongkyun Kim
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*Review Article*

# Green Communication for Next-Generation Wireless Systems: Optimization Strategies, Challenges, Solutions, and Future Aspects

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Wireless sensor networks (WSNs) have emerged as a backbone technology for the wireless communication era. The demand for WSN is rapidly increasing due to their major role in various applications with a wider deployment and omnipresent nature. The WSN is rapidly integrated into a large number of applications such as industrial, security, monitoring, tracking, and applications in home automation. The widespread use in many different areas attracts research interest in WSNs. Therefore, researchers are taking initiatives in exploring innovation day by day particularly towards the Internet of Things (IoT). But, WSN is having lots of challenging issues that need to be addressed, and the inherent characteristics of WSN severely affect the performance. Energy constraints are one of the primary issues that require urgent attention from the research community. Optimal energy optimization strategies are needed to counter the issue of energy constraints. Although one of the most appropriate schemes for handling energy constraints issues is the appropriate energy harvesting technique, the optimal energy optimization strategies should be coupled together for effectively utilizing the harvested energy. In this high-level systematic and taxonomical survey, we have organized the energy optimization strategies for EH-WSNs into eleven factors, namely, radio optimization schemes, optimizing the energy harvesting process, data reduction schemes, schemes based on cross-layer optimization, schemes based on cross-layer optimization, sleep/wake-up policies, schemes based on load balancing, schemes based on optimization of power requirement, optimization of communication mechanism, schemes based on optimization of battery operations, mobility-based schemes, and finally energy balancing schemes. We have also prepared the summarized view of various protocols/algorithms with their remarkable details. This systematic and taxonomy survey also provides a progressive detailed overview and classification of various optimization challenges for the EH-WSNs that require attention from the researcher followed by a survey of corresponding solutions for corresponding optimization issues. Further, this systematic and taxonomical survey also provides a deep analysis of various emerging energy harvesting technologies in the last twenty years of the era.

## 1. Introduction

The current era is the witness of many emerging technological advancements including the Internet of Things (IoT), cloud computing along with wireless sensor networks, and further integration of these emerging technologies for collecting and deep analysis of monitored information [1–3]. Also, this analyzed factual information is needed for enhancing the efficiency of the particular industrial system by ensuring optimal resource consumption. Moreover, for monitoring various events pertaining to home/office, human activities, health, defense, agriculture, and industries, etc., wireless sensor networks are utilized extensively [4, 5]. In extreme circumstances, sensor nodes are remotely deployed in harsh environmental conditions with the limited capacity of the battery for particular monitoring applications in which long operational periods are needed even years or decades and battery power depletes regularly with the course of time, and in these undesirable situations, it is impossible to provide battery replacement facility or recharging activity; therefore, energy efficiency is considered a major challenging issue for sensor nodes [6, 7].

To amicably handle the energy scarcity issue of sensor nodes, there is a need for an alternative energy source to compensate for the energy requirement in case of battery drain out [8, 9]. One of the best resolutions to this issue is the use of an energy harvesting technique in which energy from natural sources available in the environment is transformed into power to resuscitate the batteries [10, 11]. The new advancements in energy harvesting techniques for WSNs have become a prominent research field. But, in the case of energy harvesting, the energy output may be insufficient due to streaky and spatial variations, and some mechanisms are needed for effective utilization of the harvested energy; further, these mechanisms are collectively termed as energy optimization strategies [12, 13].

The energy harvesting wireless sensor networks (EH-WSNs) are having a large number of challenging issues based on their inherent characteristics, and these issues have a direct impact on the performance [14]. In this article, we will discuss the various challenging issues and corresponding suggested solutions in the subsequent sections, although our main focus is on energy efficiency. It is a noteworthy fact that although a large number of research have been completed and others are still going on with a proposal for enhancing energy efficiency, energy optimization has become an evergreen research challenge for EH-WSNs [15]. For EH-WSNs, there is a need for some planned mechanism known as energy optimization strategies for optimum energy consumption in a sensor node by managing energy efficiently. There exist a large number of literature focusing on energy management schemes in the last two decades; the reason is obvious; for optimal performance of WSN, there is a need for energy optimization. The ultimate aim of energy optimization strategies is to manage the energy in the network for increasing the lifetime of tiny sensor nodes, and the network remains operational perennially. Special attention is needed for managing the energy optimization issue for sensor nodes [16].

This systematic and taxonomical survey focused on discussing the energy optimization strategies for EH-WSNs. There are certain specific reasons behind this. The energy optimization strategies in EH-WSN help in achieving the desired balance between processing and transmission of data. By effectively utilizing the optimization strategies, the optimum performance can be achieved in EH-WSNs with the existence of prevailing various limitations. The term optimization in mathematical form can be defined as discovering the minimum or maximum for a particular defined function based on multiple constraints. For an optimization problem, a feasible solution is developed with the help of multiple values that satisfies all the prevailing constraints. The ultimate aim of a well-defined optimization technique is to carefully observe the feasible solutions and then proposing the optimum solution. Considering the EH-WSNs scenario with multisource energy harvesters, the design of power management circuits can be optimized for enhancing the overall efficiency. One of the most appropriate schemes for handling energy constraints issues of WSNs is the energy harvesting technique, and the proper optimization of EH technologies and devices is needed; further, the optimal energy optimization strategies should be coupled together for effectively utilizing the harvested energy.

*1.1. A Distinctive Approach and Motivation.* In this article, we have done an extensive study for classifying the energy optimization strategies for EH-WSNs; the uniqueness in this research that distinguishes this work from others is the in-depth classification of energy optimization strategies for EH-WSNs by covering all possible aspects. Also, in this article, different energy optimization strategies have been discussed consisting of various algorithms along with further details of improvements in the coming future.

Although, there exist a large number of literature on energy management issue that mostly focus on a particular area and discuss energy management by considering only particular perspective and they do not concentrate on other areas affecting energy utilization in EH-WSNs, and we have tried our best to overcome this drawback of existing pieces of literature and try to cover as many as possible all perspectives in this article. We hope that the energy optimization strategies discussed in this article with a wide view definitely help the researchers working on this area to understand the key pillars of the energy optimization framework. Further, this article also provides space to explore new possibilities for energy efficiency in the field of EH-WSNs.

*1.2. Salient Contributions towards Findings.* In this systematic review article, we have conducted a detailed study of energy optimization issues in EH-WSNs. The detailed study helps in finding the facts (research gaps) in the existing review papers and guides the authors to write a systematic review article covering all aspects related to energy optimization for EH-WSNs.

The major contribution of this systematic review article can be pointed out as follows:

(1) This systematic review article explains the energy optimization strategies for EH-WSNs by considering eleven factors, namely, radio optimization schemes, optimizing the energy harvesting process, data reduction schemes, schemes based on cross-layer optimization, sleep/wake-up policies, schemes based on load balancing, schemes based on optimization of power requirement, optimization of communication mechanism, schemes based on optimization of battery operations, mobility-based schemes, and finally energy balancing schemes. The ultimate aim is to discuss the energy optimization schemes for EH-WSNs with a diversified view covering all possible areas having the sharp vision that affected the energy consumption in the network

(2) Furthermore, this systematic review article provides the pointwise precise overview of various key pieces of literature in the last twenty years covering especially duty cycle schemes, MAC protocols, opportunistic routing schemes considering geographic characteristics, cluster-based routing, and also energy balancing schemes with key attributes

(3) Next, this systematic review article provides complete coverage of challenging issues for formulating the optimization problems for EH-WSNs and also describes the solutions to optimization problems in the form of popular algorithms

(4) Further, this systematic review article provides the paradigm shift for energy harvesting technologies considering the twenty years of an era starting from the year 2000 to 2020 and also describing the next-generation technologies and future of energy harvesting techniques

We have structured this systematic review article as per the following: Section 1 comprises the brief introduction of WSNs, the need and role of energy harvesting techniques, and WSNs with energy harvesting techniques (EH-WSNs), and in the last, this section describes the need of energy optimization strategies for EH-WSNs. Section 2 provides a deep insight into the adopted research methodology. In Section 3, this article provides details about the energy harvesting techniques with corresponding sources of energy. In Section 4, this article provides the classification of energy optimization strategies with a broad view by covering multiple factors; also, the precise tabular representations of duty cycle schemes with key attributes, MAC protocols, opportunistic routing schemes considering geographic characteristics, key features of clustering approaches, and also energy balancing schemes are illustrated. The optimization problems with the respective solutions for EH-WSNs are provided in Section 5. Also, a paradigm shift for energy harvesting technologies along with the future of energy harvesting techniques for WSNs and further research directions is provided in Section 6. In Section 7, this review article provides a conclusion.

## 2. A Deep Insight into the Adopted Research Methodology

This systematic review article focuses on the energy optimization strategies for EH-WSNs with a broad view by covering all possible factors that affected the energy efficiency in EH-WSNs.

There exist a large number of literature with a focus on performance enhancement for EH-WSNs; further, it should be noted that researchers have already put lots of efforts towards proposing various strategies for EH-WSNs for enhancing the performance by covering the energy scarcity issue. We would like to highlight a few pieces of literature as [17–20]. We have tried our best level to select the appropriate literature for conducting the detailed study for collecting facts and thereby designing this systematic review article.

We have selected the era starting from 2000 to 2020 for selecting the appropriate good literature with good citations. Articles published in different journals/conferences have been studied for collecting the facts about energy optimization. Figure 1 illustrates the number of literature considered yearwise.

We have adopted a structured research methodology consisting of six major steps as depicted in Figure 2. In this systematic review article, we have structured the research into six major steps:

In step 1, we select the potential research questions, and further, we understand the need of exploring the research questions; next, we define the research objectives corresponding to potential research questions. Further, in step 2, we prepare the new database consisting of high-quality research papers from three already existing databases, namely, Web of Science, SCI/SCIE, and Scopus databases, and next, we conduct an extensive research study which leads to further retrieval of data for formulating systematic research design. Furthermore, in step 3, we prepare the summarized solutions corresponding to research questions with the help of an analyzed literature review. Next, in step 4, we perform the quality assessment activities for verifying the facts and figures which we have collected from the newly constructed database. This step is very important because this systematic review article will provide significant information to researchers working on the energy optimization issues of EH-WSNs. Moreover, in step 5, we prepare the summary of outcomes after analyzing the literature in the newly constructed database. Besides, in step 6, we mark the corresponding references.

The newly constructed database consists of various literature, and we have considered three major parameters while considering the particular literature for this systematic review and three parameters are the articles that should focus on our primary objective, i.e., energy efficiency, the journal in which literature has been published that should be peer-reviewed, and next, the selected literature that should have appropriate citations.

Initially, we have selected 610 pieces of literature. After, the analysis we have further selected 305 pieces of literature out of the database of 610 pieces of literature. Again, we perform further analysis and select 178 pieces of literature out of 305 pieces of literature previously selected.

## 3. Energy Harvesting Techniques with Corresponding Sources of Energy

The major issue that has a severe impact on the performance of WSNs is the evergreen energy scarcity issue that needs to be handled with a focused approach. Traditionally, sensor nodes are operating with limited capacity batteries and batteries are having their limitations such as leakages of current, breakdown issues, and limited energy density issues. Also, the sensor nodes energy profile is regularly depleted with the time; thereby, sensor node is not able to provide the assigned duties especially in longer duration, but there exist many applications which require a much higher lifespan of sensor nodes ranging from months to several years, so in

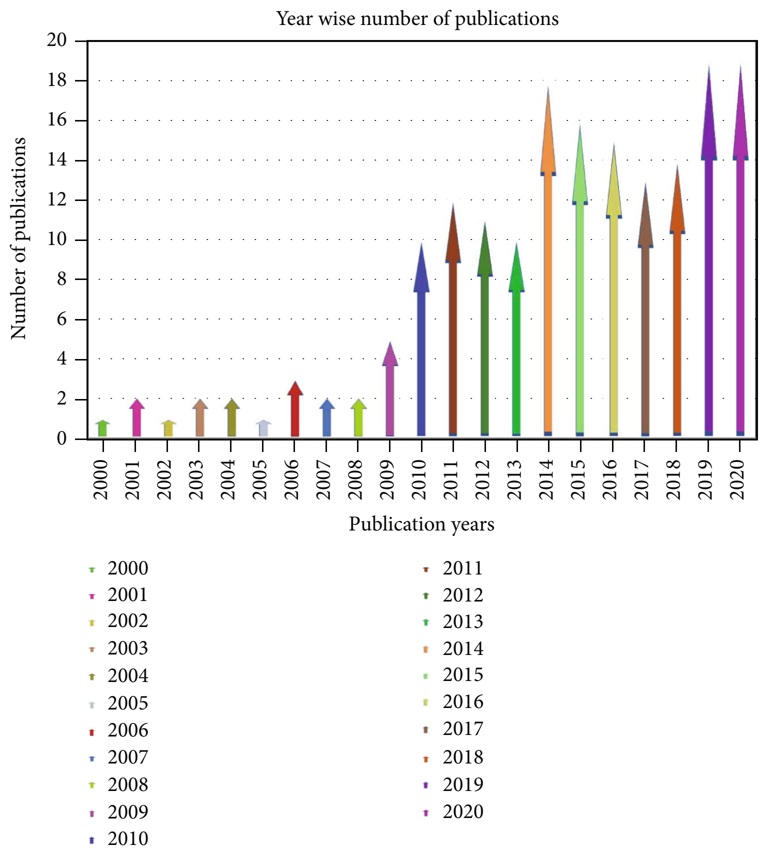


Figure 1: Yearwise number of literature considered for maintaining the database.

these emergencies, there exist only two usual solutions in terms of replacing the batteries or harvesting the energy to fill the gap that arises due to depleted energy. Also, battery replacement is sometimes not possible especially in cases of difficult remote deployment. So, the most general solution for enhancing the life of sensor nodes is by providing a regular power supply and further this is possible by utilizing the energy harvesting mechanism and this scheme enables the sensor nodes to work continuously without interruption, since, in most cases, sensor nodes need a continuous power supply. Further, Figure 3 describes the different types of energy harvesting mechanisms with different energy types available for harvesting and Table 1 illustrates the power density of various energy harvesting schemes.

Next, we are trying to illustrate the brief description with relevant references as per the following.

Mechanical energy harvesting [21, 22] is defined as the method in which energy conversion from mechanical to electrical occurs. The harvester consists of the spring-mounted mass component installed inside, and the mechanical energy from displacements and oscillations is converted into electrical energy. This entire process utilized mechanical stress, vibrations, rotational movements of waste, fluid, force, and high-pressure motors. There exist three forms of mechanical energy harvesting, namely, electromagnetic, electrostatic, and piezoelectric. In the piezoelectric energy harvesting method [23, 24], the two factors play a major role such as the use of piezoelectric material and the piezoelectric effect. Here, the piezoelectric material is strained, and further, energy from vibrations, pressure, and force is converted to electrical energy. The electrostatic energy harvesting mechanism [25] utilized the principle in which energy conversion occurs from mechanical to electrical with the capacitance change. Here, the key factor is changing the capacitance of a varying capacitor which is depending on the vibrations. Next, the popular law of electromagnetic induction which is known as Faraday's law is used in the electromagnetic energy harvesting mechanism [26, 27]. Here, the electromagnetic harvester utilizes the inductive spring-mass system which is the backbone of this type of harvesting system. The stationary magnet creates the magnetic field, and further, movement of magnetic material via the magnetic field induces the voltage. Now, energy conversion takes place from mechanical energy to electrical energy.

Photovoltaic energy harvesting is defined as the method in which conversion of photons to electrical energy occurs, and here, photons are coming from sources such as artificial or solar light. In this harvesting mechanism, photovoltaic cells are exploited. Here, at the P-N junction, an electrical field is formed [28]. The solar energy harvesting mechanism is illustrated in Figure 4.

Thermal energy harvesting [29] can be implemented in two ways as pyroelectric and thermoelectric energy harvesting. Further, thermoelectric energy harvesting consists of power generators that are used for electrical energy generation based on the Seebeck effect and known as thermoelectric

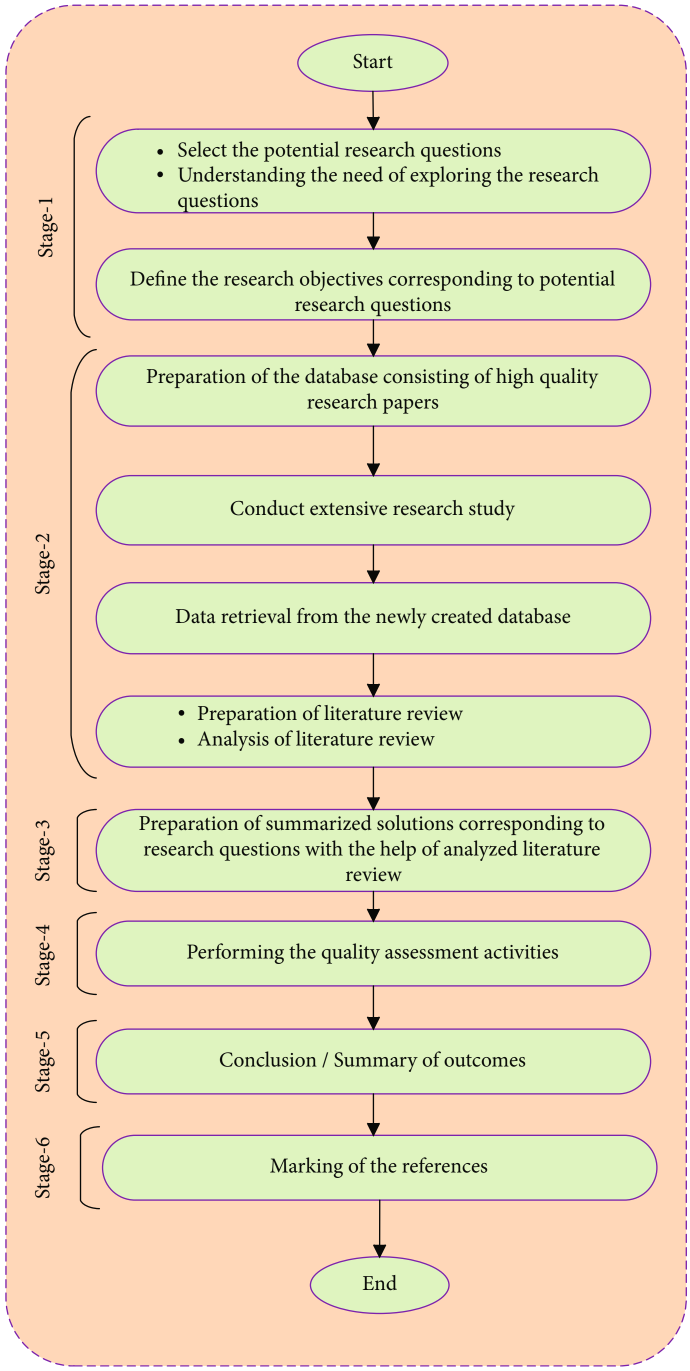


Figure 2: Structured research methodology with six major steps.

power generators. The thermopile is the main element of a thermoelectric power generator. Further, two dissimilar conductors' arrays are used in the formation of the thermopile [30]. Pyroelectric energy harvesting is defined as the method in which voltage is generated by cooling or heating the pyroelectric materials. The basic core element of pyroelectric energy harvesting is the pyroelectric material's crystal structure, and due to change in temperature, atom location in crystal structure changes and which further results in producing the voltage. Pyroelectric materials require time-varying changes in the temperature as compared with thermoelectric energy harvesting in which temperature gradient is needed [31].

Wireless energy harvesting exists in two major forms such as resonant and RF energy harvesting. Further, RF energy harvesting consists of a rectifying antenna or rectenna which is used for converting electromagnetic waves into electrical energy. In the RF energy harvesting mechanism, there are two sources from which energy can be harvested either through RF power or through electromagnetic signals with a specific wavelength. Further, sources, namely, microwaves, cell phones, broadcasting of television and radio, and Wi-Fi,

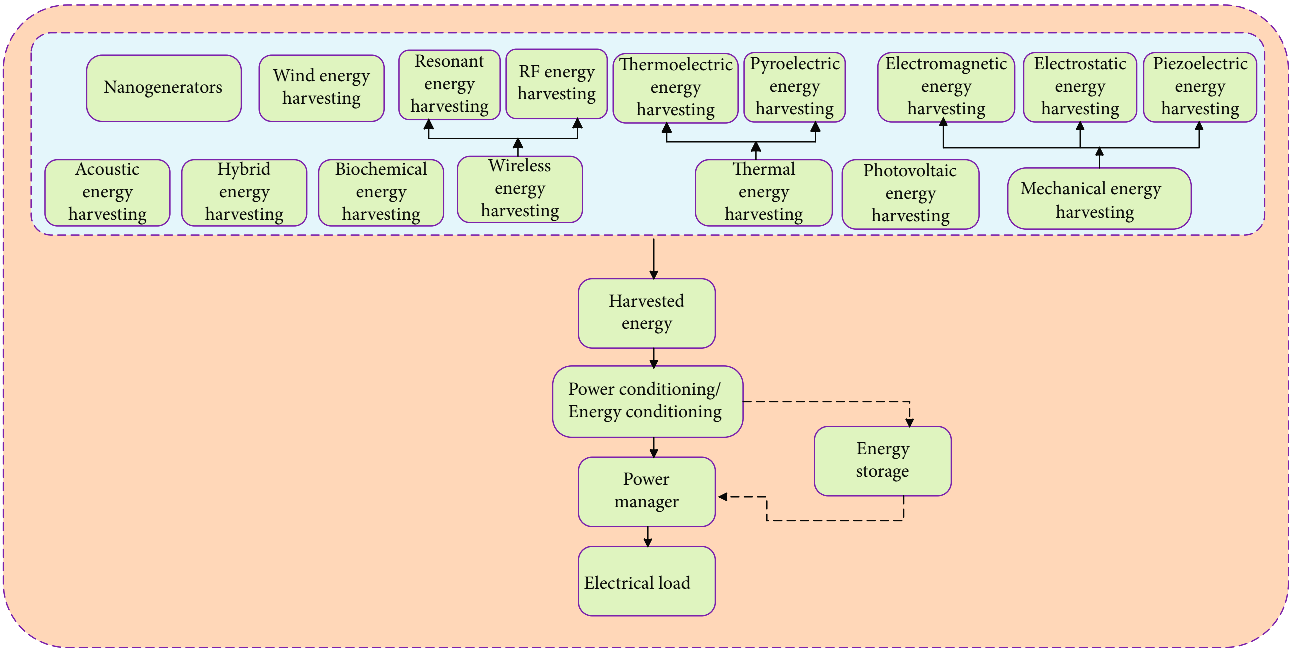


Figure 3: Energy harvesting techniques with corresponding sources of energy.

Table 1: Power density of various energy harvesting schemes [14].

| Source of energy | Classification | Energy harvesting methodology | Power density |
|---|---|---|---|
| Mechanical energy | Motion | Electromechanical | 330 $\mu$W/cm$^3$ |
| | Acoustic noise | Piezoelectric | 960 nW/cm$^3$ |
| | Hydro & flow of wind | | 16.2 $\mu$W/cm$^3$ |
| Thermal energy | Heat from body | Thermoelectric | 40 $\mu$W/cm$^2$ |
| Energy from radiation | Solar energy | Solar cells | (Indoor) <10 $\mu$W/cm$^2$ (Outdoor) 15 $\mu$W/cm$^2$ |
| | RF | Electromagnetic conversion | (GSM) 0.1 $\mu$W/cm$^2$ (Wi-Fi) 0.01 $\mu$W/cm$^2$ |

are considered as ambient RF power. Resonant energy harvesting or resonant inductive coupling can be defined as the method of transmitting and accumulating electrical energy specifically between the two coils. There exist two coils named primary and secondary coil; further, an inductive transformer is attached to a primary coil. At the same frequency, these two coils are resonant. Next, through the air, power is sent to a specified device that is attached to a secondary coil. The magnetic flux is produced by the primary coil which is time-varying in nature, and further, voltage is induced whenever that magnetic flux crosses the secondary coil [32]. RF energy harvesting is depicted in Figure 5.

Wind energy harvesting is defined as the method in which the conversion of energy from airflow or wind energy to electrical energy occurs. In wind energy harvesting, a specified-sized wind turbine is used. Further, the wind turbine exploited the linear motion due to wind for the generation of electrical power [33]. Wind energy harvesting is explained in Figure 6.

Biochemical energy harvesting is defined as the method in which electrochemical reactions are used for the conversion of endogenous substances and oxygen to electrical energy [34].

Acoustic energy harvesting is defined as the method in which a resonator or transducer is used for the conversion of acoustic waves to electrical power [35]. Acoustic energy harvesting is illustrated in Figure 7.

Hybrid energy harvesting is defined as the method of combining any harvesting technologies and further concurrently using this hybrid model on a single platform. The concept of hybrid energy harvesting is illustrated in Figure 8.

In the current era of IoT, nanoenergy-based technology is booming which is known as nanogenerators. Further, nanogenerators are having the capability of harvesting energy from the surroundings and efficiently utilizing that harvested energy for facilitating the tiny sensors and other portable electronic devices. In a more general way, we can define the nanogenerators as the energy harvesting device for generating electrical energy from ambient mechanical energy. The nanogenerators are classified into four major categories such as piezoelectric nanogenerators (PENGs), triboelectric nanogenerators (TENGs), thermoelectric generator (TEGs), and

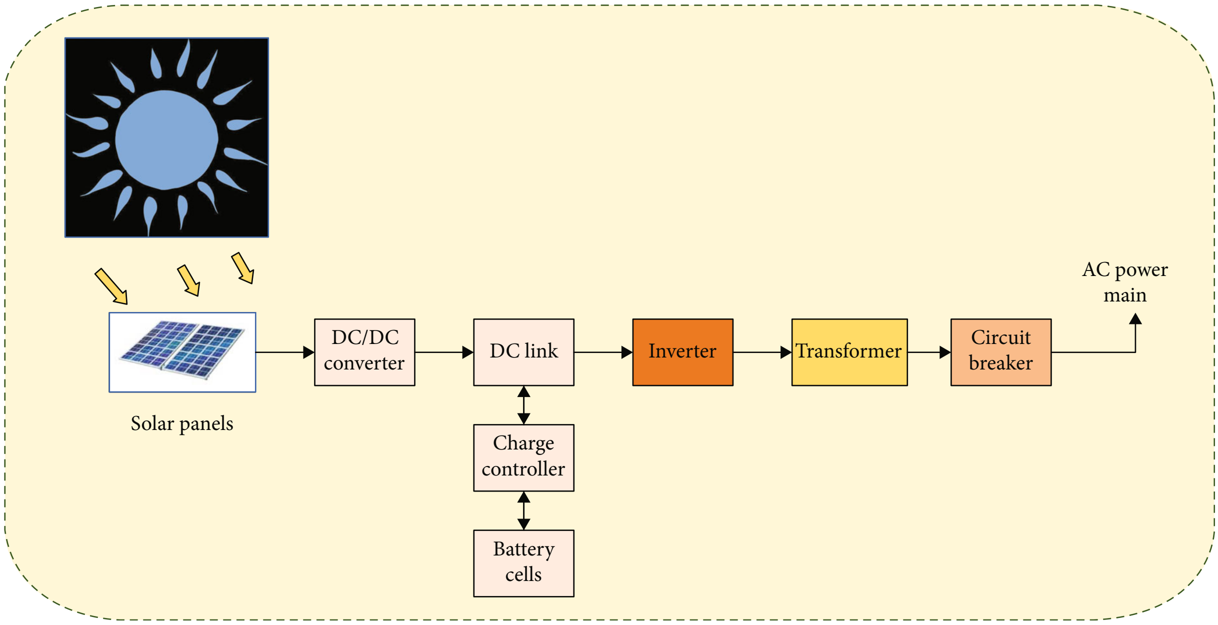


FIGURE 4: Solar energy harvesting mechanism.

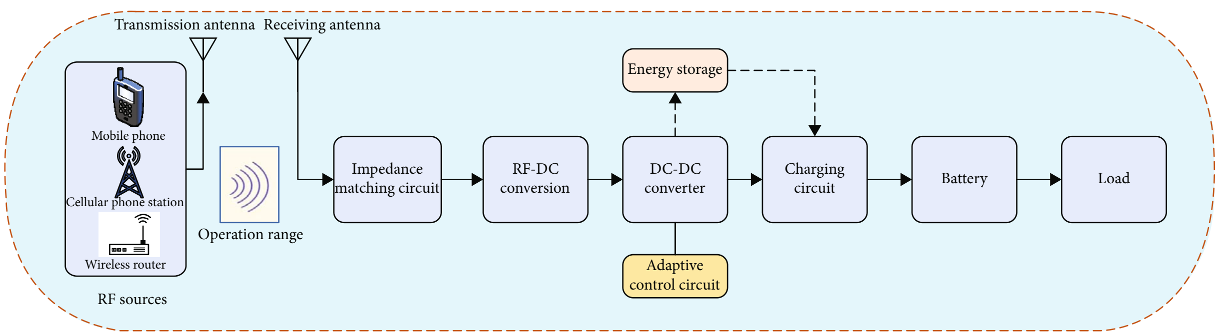


FIGURE 5: RF energy harvesting mechanism.

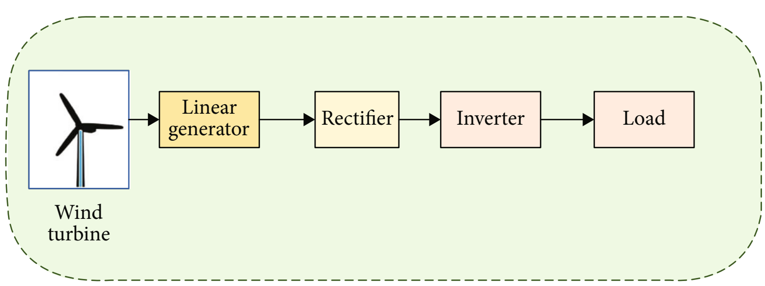


FIGURE 6: Wind energy harvesting mechanism.

pyroelectric nanogenerators (PyENGs) which are based on piezoelectric, triboelectric, thermoelectric, and pyroelectric effects, respectively. Further, piezoelectric nanogenerators (PENGs) are based on the piezoelectric effect. Next, the mechanism of triboelectrification, as well as electrostatic induction, is utilized in triboelectric nanogenerators (TENGs). Whenever the two dissimilar materials are brought into contact, then the charge is generated on the surface; this complete mechanism is known as triboelectrification; on the other hand, in the electrostatic induction mechanism, the flow of electrons from one electrode to another electrode through an external load causes an electricity generation. Furthermore, thermoelectric generators (TEGs) utilized the phenomenon of converting the temperature difference into electric voltage. Besides, pyroelectric nanogenerators (PyENGs) utilized nanosized pyroelectric materials for converting thermal energy to electrical energy; therefore, pyroelectric nanogenerators (PyENGs) are considered as

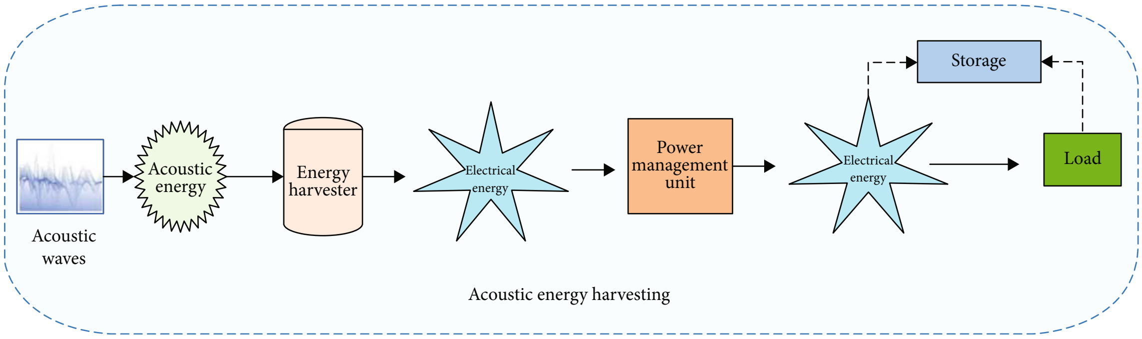


FIGURE 7: Acoustic energy harvesting mechanism.

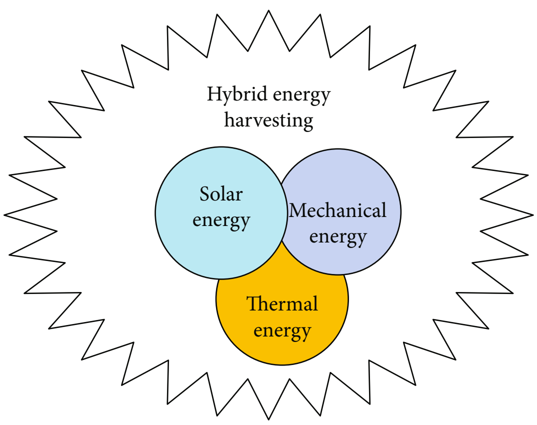


FIGURE 8: The concept of hybrid energy harvesting mechanism.

futuristic energy harvesting devices with enormous capability [36, 37].

Furthermore, in the case of a linear and rotatory generator for energy harvesting [38, 39], the motion of the wave provides irregular mechanical energy. Further, this form of mechanical energy is needed to convert into regular mechanical motion. Next, there exist two types of motions, namely, linear or rotational. The rotational motion is dedicated for driving a turbine, and then, the rotating electrical generator is driven. But the linear motion is responsible for driving a linear electrical generator. Figure 9 illustrates the role of linear generator in converting ocean wave energy to electrical energy.

In the energy harvesting mechanism, there exists specific hardware which is known as an energy harvester and it is responsible for converting the environmental energy to electrical energy. Further, there is a need for efficient conversion of harvested energy to electrical energy and then appropriately conditioned by the power management circuit to an appropriate form then energy is stored in the energy storage elements, and finally, electrical energy can be utilized either for energizing the batteries or directly providing the supply to the load.

*3.1. Role of Energy Harvesting Techniques in WSNs.* The energy harvesting techniques have played a significant role in uplifting the overall performance of WSNs. The summary of key benefits is elaborated in a pointwise fashion in the following section.

(1) The energy harvesting technique in WSN provides an alternative source of energy to sensor nodes (SNs) by utilizing the harvested energy from the environment, and in this way, this technique plays a major role in reducing the dependency on battery power. One of the main research areas in the field of WSN is energy efficiency, and various mechanisms have been developed to reduce the power consumption of SNs. The harvested energy may be used sufficiently for sensor node operation and further this technique can eliminate the use of the battery

(2) WSN is specially deployed in risky environments for sensing particular events in which regular access to sensor nodes is very difficult or even not possible after deployment; here, a continuous power supply is needed for the sensor node's operation and this is only possible by utilizing energy harvesting technology in WSN. Sensor nodes can operate continuously by utilizing harvested energy from natural sources from environments

(3) WSN is deployed with the aim for long-term uninterrupted monitoring of a particular event, and this is the primary goal of any already deployed WSN. The energy harvesting technique can fulfill this aim by providing a continuous supply of energy to sensor nodes till the harvested energy is available from the environment; with this technique, sensor nodes can perform their basic tasks for decades

(4) Traditional WSNs are suffering from the high cost of maintenance. In these WSNs, the maintenance mechanisms consist of replacing a large number of batteries in due time and also regular visits to sites for checking the health of batteries. This maintenance cost can be significantly reduced by using energy harvesting techniques. No regular visits are needed in the case of EH-WSNs; also, energy harvesting eliminates the general need for batteries, and therefore, in this technique, the costs of maintenance are significantly decreased

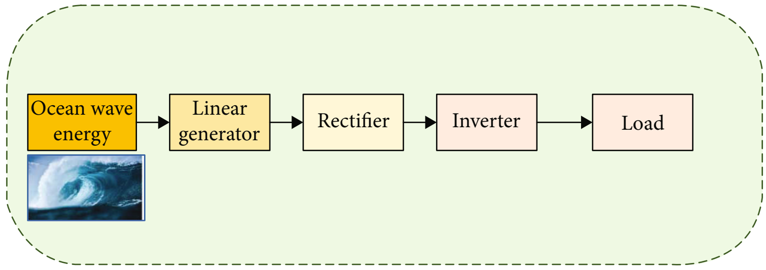


Figure 9: Ocean wave energy converted to electrical energy.

(5) The overall average cost of installation for WSN having an energy harvesting mechanism is low as compared with traditional WSN, although there is a need for harvester circuits and other hardware devices that add a particular cost to the installation. The overhead in the installation is also low in the case of EH-WSN

## 4. Classification of Energy Optimization Strategies for EH-WSNs

In traditional WSN, the remotely deployed energy constraint sensor nodes (SNs) require optimal energy optimization strategies for efficient utilization of capabilities of WSNs. Generally, traditional sensor nodes (SNs) are powered by limited capacity batteries that are attached to SNs and the use of SNs are particularly useful in an isolated and remote area, but the limited energy capabilities of SNs affected the performance in these remote areas. Further, in harsh challenging environmental conditions, it is very difficult or impossible to replace the batteries or energizing the batteries. Therefore, WSNs, which are powered by conventional batteries, are not able to provide long-lasting performance. The issue of the limited capacity of battery power has shifted the attention of researchers towards finding alternate sources of energy to energize the SNs by harvesting ambient energy. Therefore, the life span of WSN can be enhanced by utilizing the emerging technologies known as energy harvesting schemes, and further, energy optimization strategies can be used to effectively utilize the energy harvesting techniques. Also, these mechanisms achieve balance in the energy for the overall network.

The uniqueness in this systematic survey is that we have considered the two views while conducting the survey, first considering the current enhancements in energy optimization strategies while in parallel comparing with the traditional approaches for handling energy scarcity issues. This overall systematic survey broadly consists of two branches, namely, energy harvesting techniques coupled with energy optimization strategies for efficiently utilizing the harvested energy.

The aim of conducting the survey about energy optimization strategies is to handle the challenging issue of energy scarcity, and in this way, we can keep the sensor nodes alive making the network more operational and efficient. It must be noted that in this systematic survey, we have studied the internal design details of the protocol with energy-saving capabilities for understanding the limitations with abilities in dealing with the system with energy harvesting characteristics.

The role of energy optimization schemes for EH-WSNs is eventually to save energy which is considered as the primary issue for the EH-WSNs for achieving the specified objective. Extensive deep studies have been conducted for the classification of energy optimization schemes for EH-WSNs in the following categories by considering eleven factors, namely, radio optimization schemes, optimizing the energy harvesting process, data reduction schemes, schemes based on cross-layer optimization, sleep/wake-up policies, schemes based on load balancing, schemes based on optimization of power requirement, optimization of communication mechanism, schemes based on optimization of battery operations, mobility-based schemes, and finally energy balancing schemes. The ultimate aim is to discuss the energy optimization schemes for EH-WSNs for achieving energy efficiency by decreasing energy consumption and also achieving energy balance among sensor nodes. Figure 10 depicts the deep classification of energy optimization schemes for EH-WSNs.

*4.1. Radio Optimization Schemes.* Radio optimization schemes are further divided into three categories such as schemes based on power control in transmission, cooperative communication schemes, and also modulation optimization schemes. A brief discussion about all these schemes is provided below.

In WSN, one of the main units in which heavy energy consumption occurs is the radio module. Therefore, some power control mechanism is needed for transmission. In the adaptive transmission power control framework, a separate model representing the relationship between power needed for particular transmission and corresponding quality of the link is built by the separate node for their neighbors. Further, these models help in maintaining link quality over a period of time dynamically with the help of a feedback-based algorithm for power control in transmission [40].

Next, for designing optimal WSN, optimization of energy is a crucial factor that needs to be carefully addressed. Also, in WSN, the energy consumption part in the circuit module as compared with actual energy consumption that occurs in the transmission part may not be negligible, and further, both these parts need to be recorded separately. Therefore, the general optimization techniques for energy may not be sufficient in the case of WSN, which are responsible for reducing the energy in the transmission process. Also, it has been

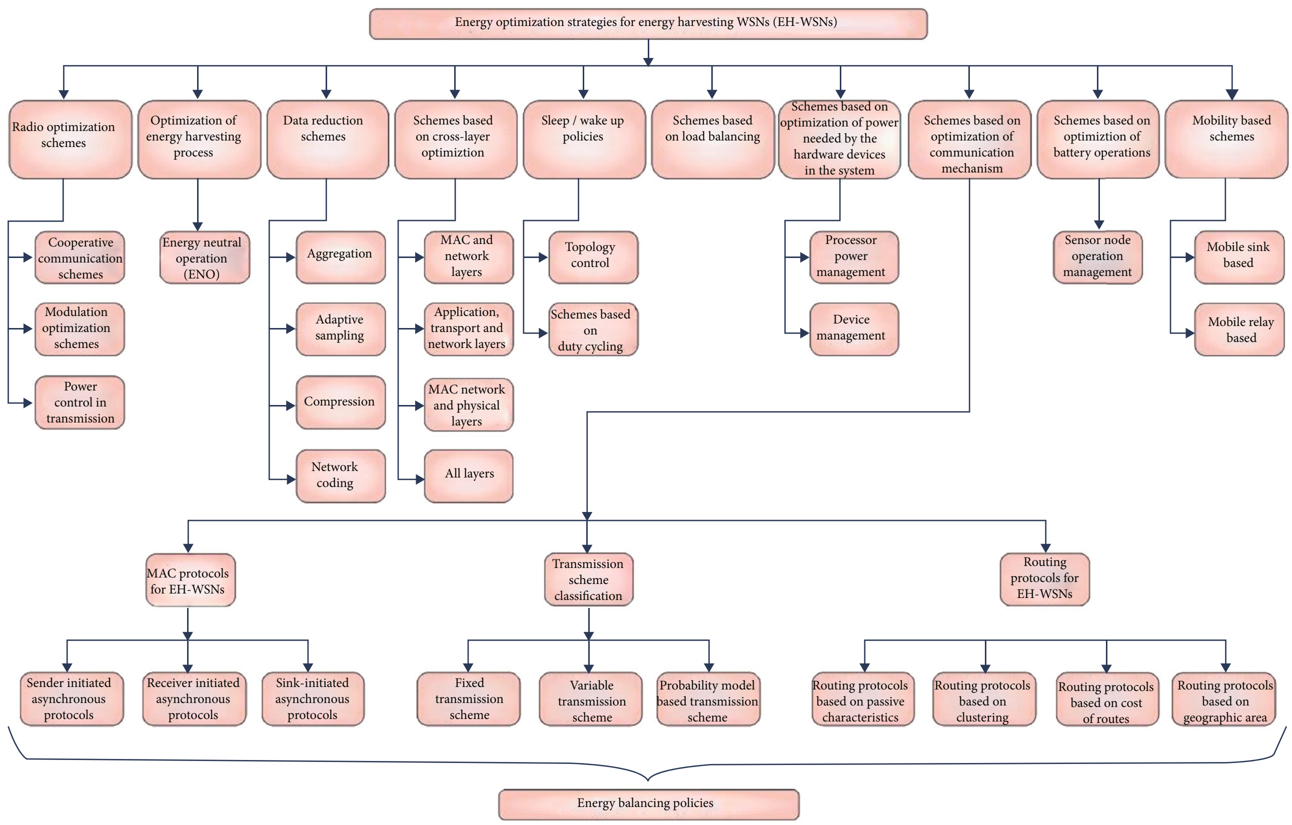


Figure 10: Deep classification of energy optimization schemes for EH-WSNs.

proved in the literature that two prominent factors, namely, energy consumption and delay in transmission, can be minimized under the cooperative environment among the sensor nodes in WSN for transmitting and/or receiving information [41, 42].

Next, it should be noted that in communication link with point-to-point connection and for applications having shorter distance, one traditional fact that higher transmission duration results in minimum energy consumption may be false if energy consumption in circuit module is significantly considered. Also, the transmission time should be maximum in order to minimize the energy requirement in the transmission process. Further, there is a need of optimizing the transmission time for overall minimizing the total energy consumption in WSN [43, 44].

*4.2. Optimization of Energy Harvesting Process.* The research area towards the energy harvesting techniques is getting much higher attention by the researcher currently, and lots of research is going on exploring the optimal use of energy harvesting technique. The research activities on energy harvesting area can be broadly categorized into two categories such as optimal design and development of energy harvesting framework, and next category deals with efficiently storing the generated charge and this is possible only by proficiently designed capable electronic circuits. The microelectronic devices used in the harvesting process need to be optimized for reducing the overall energy consumption in the system. There exist a large number of literature discussing the optimization of energy harvesting mechanism; we are highlighting a few of the literature as follows.

Buchli et al. [45] have presented a unique scheme for dynamically adjusting the performance level of the system by designing an efficient power subsystem, and in this way, uninterrupted energy-neutral operation can be achieved in solar EH-WSNs. Next, Reis et al. [46] have discussed about the need of optimizing the extraction circuits for efficient utilization of the energy harvesting mechanism. Further, Tai and Zuo [47] have conducted a two-variable optimization analysis for deriving the exact optimization conditions for maximum power. Furthermore, Cai and Harne [48] have proposed an optimal optimization framework at the system level, particularly for a nonlinear vibration energy harvester. Besides, Fouad [49] has discussed the important role of the rectifier in energy harvesting applications and proposed an efficient CMOS rectifier.

*4.3. Data Reduction Schemes.* The data reduction schemes can be further classified as schemes based on aggregation, compression, adaptive sampling, and also network coding. A brief discussion about all these schemes is provided below.

In WSN, one of the ways to save energy is by efficiently handling the transmitted data. The aim of data aggregation schemes is to collect the sensitive data from the sensor nodes in the network and further sent it to the base station with lower data latency. Environment monitoring requires fresh data, and therefore, data latency is playing a crucial role in various monitoring applications [50]. It is a very tedious step or even impossible to access all original data after performing the aggregation function. The success of gaining original data depends on the type of aggregation function. There are two approaches, namely, lossy and lossless. In the lossless approach, there exists a high possibility of gaining the original data without error. For selecting a particular approach, various factors need to be evaluated such as application area, rate of data transmission, and network characteristics [51].

Further, the data samples should be minimum for energy conservation schemes. The impact of reduced data samples also results in the decrement of the total number of communications and thereby maintaining energy efficiency. Further, spatiotemporal correlations can be utilized for reducing the data samples and such type of scheme is known as adaptive sampling. Here, a joint approach covering the features of both temporal and spatial correlations can be used to minimize the total amount of data that is needed to be acquired [52]. Furthermore, in WSN, the number of transmissions can be further reduced by using the characteristics of multiple data packets coding scheme. This mechanism results in a reduced number of transmissions because multiple data packet coding occurs within a single transmission [53].

*4.4. Schemes Based on Cross-Layer Optimization.* The cross-layer optimization schemes can be further classified as MAC and network layers; application, transport, and network layers; MAC, network, and physical layers; and finally all layers. A brief discussion about all these schemes is provided as follows.

Bouabdallah et al. [54] have presented a joint cross-layer framework considering MAC and network layers. For enhancing the lifetime of the network, energy-efficient protocols are needed. They proposed the scheme for traffic balancing at the network layer, and further, they proposed another scheme for controlling the retry limit of retransmissions at the MAC layer. In the proposed framework, energy efficiency is achieved by controlling the retry limit and thereby contributing towards enhancing the lifetime of the network.

You and Liu [55] have formulated a problem for maximizing the lifespan of the network which is known as a cross-layer problem. The counterpart of the formulated cross-layer problem can be decomposed into several individual subproblems such as problem for the application layer with the focus on improving the lifetime, problem for transport layer with the focus on controlling the source rate, and problem for network layer with the focus on optimizing the routing efficiency. Further, the subgradient methods are used for solving the dual problem.

Lee et al. [56] have presented a cross-layer optimization framework for improving system performance. Further, they suggested that this joint optimization framework efficiently handles the communications especially in the case of delay-constraint applications. The mechanism of the proposed cross-layer optimization framework can be illustrated with consideration of different individual protocol layers such as MAC layer for power allocation, network layer for optimal routing, and physical layer for energy management.

Phan et al. [57] have presented a cross-layer design in the form of an optimization problem with two stages. The first stage of the optimization problem is dedicated for maximizing the total number of admitted sensor nodes. Further, the second stage is aimed at enhancing the network lifetime. Therefore, this cross-layer design is covering all layers. Next, they have also shown that the optimization problem having only one stage with a compact and precise mathematical framework can be derived from the two-stage optimization problem.

*4.5. Sleep/Wake-Up Policies.* The sleep/wake-up policies can be further classified as schemes based on topology control and also schemes based on duty cycling schemes. A brief discussion about topology control schemes is provided as follows.

Topology control framework is aimed at maintaining efficient connectivity or coverage in WSN. In this framework, each sensor node dynamically adjusts the power for optimal transmission. Also, each sensor node selects the appropriate neighboring sensor nodes set for direct communication. All these steps in the topology control framework contribute towards the conservation of energy at each sensor node and consequently enhance the network lifetime.

The optimal deployment of WSN requires careful handling of two crucial factors, namely, network coverage and connectivity. Further, area monitoring applications need proper coverage of networks with efficient connectivity; therefore, the success of area monitoring applications primarily depends on these two prominent factors. Also, there may exist a probability of coverage area redundancy issue and this redundancy should be minimum for optimal resource utilization by the resource constraints sensor nodes in the WSN [58]. Next, the cooperative topology control framework has been presented in [59] and this framework is a distributed topology control scheme with the objective of maximizing the overall lifetime of the network.

Next, a detailed review for duty cycling schemes is provided in tabular form as described in Table 2.

*4.6. Schemes Based on Load Balancing.* A brief discussion about various schemes based on load balancing is provided below.

Liu et al. [92] present various strategies for enhancing the performance of EH-WSNs with a focus on three areas, namely, efficient scheduling, energy-efficient relaying, and finally optimizing the medium access control layer protocols. Next, Cai et al. [93] have presented a new routing algorithm for EH-WSNs in which the flow of load is maximized under the life span of the network; also, in this framework, energy consumption is balanced for prolonging the lifetime of the network. Here, residual energy is considered as a prominent factor for updating the transmission capacity between any two particular sensor nodes. Further. Wu et al. [94] have proposed an efficient energy-balanced routing framework that is based on an autonomous load regulating scheme for rechargeable WSN. In this framework, significant steps are taken to control the relay radius, and consequently, nodes become capable of adjusting their load. Furthermore, Chai and Zeng [95] have presented a routing scheme for EH-WSNs with efficient load balancing characteristics. This

Table 2: A detailed review of duty cycling schemes for EH-WSNs.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| 2004 | Kansal et al. [60] | Latency factor | (i) An analytically tractable characterization model is proposed.<br>(ii) Also, a harvesting theory is proposed.<br>(iii) Further, a solar energy harvesting circuit is proposed.<br>(iv) Furthermore, environment-aware tasking methods are proposed. | (i) The future research directions may include the steps for finding the appropriate framework consisting of estimation for the source characterization parameters with multiple energy harvesting techniques. |
| 2006 | Hsu et al. [61] | Utilization of energy | (i) An adaptive duty cycling algorithm is presented.<br>(ii) In the proposed framework, the available energy is used for adjusting the duty cycle of sensor nodes. | (i) Future work may include extending the proposed methods to exploit different power scaling frameworks, namely, dynamic voltage scaling (DVS), submodule power switching (SPS), and the use of multiple low power modes (MLPM). |
| 2007 | Moser et al. [62] | Violation of deadline | (i) An energy-driven scheduling scenario is presented.<br>(ii) The energy variability characterization curves (EVCC) have been introduced in this article. | (i) Future work may include extension towards multihop networks.<br>(ii) Need for distributed energy management solutions. |
| 2010 | Lee et al. [63] | Throughput | (i) A duty cycling scheme is presented with awareness about the harvesting mechanism.<br>(ii) In the proposed framework, the sleep time is adjusted dynamically. | (i) Future work may include extending the works towards the multihop data delivery scheme.<br>(ii) Further, future research directions include efforts towards the in-depth analysis of the energy harvesting process for transmission strategies. |
| | Li et al. [64] | Packet delivery ratio | (i) The scheduling problem is defined in terms of a partially observable Markov decision process.<br>(ii) This article also presents that the formulated scheduling problem can be portioned as Markov decision process (MDP). | (i) The simulations are based on a single group consisting of the source node, relay, and destination node. Future work may include an extension towards considering multiple groups.<br>(ii) Future work may also include some more performance evaluation metrics. |
| 2011 | Ghor et al. [65] | Energy storage capacity & deadline miss rate | (i) An online scheduling mechanism is presented which is known as the earliest deadline with an energy guarantee (EDeg).<br>(ii) Further online scheduling mechanism characterizes various objectives such as the source of energy, energy storage, energy consumption, and total time. | (i) Future work may include the extension towards expanding the applicability of the scheduling framework by incorporating various techniques, namely, voltage scaling, frequency scaling, and dynamic power management, and then measuring the effectiveness of the proposed scheme. |
| | Audet et al. [66] | Violation rate of energy & battery charge level | (i) In this article, two scheduling algorithms have been presented, namely, smooth to average method (STAM) and smooth to full utilization (STFU).<br>(ii) Further, these two scheduling algorithms are energy-aware and reduce the task violation likelihood. | (i) The future work may include an extension towards evaluating the proposed scheme by incorporating the data acquisition application. |
| 2012 | Györke and Pataki [67] | Energy consumption | (i) This article suggests that a scheduling system with prediction capability should be used in | (i) The future research work may include the work towards performing the real-life testing of our assumptions. |

Table 2: Continued.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | | | dynamically determining the sensors' measurement timing.<br>(ii) This framework must have previous information about factors such as environment, sensors, experiments, and also about future prediction. | (ii) Further, our future research directions will refine the scheduling framework to generate more accurate outputs with fewer energy consumptions. |
| | Kooti et al. [68] | Violation count for QoS | (i) This article proposes an efficient energy management framework for enhancing QoS.<br>(ii) The framework consists of dual steps, an offline step, and an online step.<br>(iii) Next, prediction with frame-based energy harvesting is used for determining the appropriate QoS level in an offline step. | (i) This article utilized the window-based QoS model in which deadline misses are handled by specific distribution patterns.<br>(ii) Future work may include considering random/general distribution patterns for the window-based QoS model. |
| | Renner and Turau [69] | Root mean square error (RMSE) | (i) This article proposes the framework for replacing the static scheme for enhancing the effectiveness of existing forecasting algorithms. | (i) The future work may include an extension towards improving prediction quality.<br>(ii) The future work will focus on the global information consisting of cloud cover or snow warnings that can be used for enhancing the accuracy in long-term prediction. |
| 2013 | Akgün and Aykın [70] | Life span of network | (i) This article proposes a framework for enhancing the life span of the network.<br>(ii) In this framework, the scheduling scheme based on TDMA has been modified, and in this modified scheduling scheme, members will request a time slot based on their energy prediction.<br>(iii) Next, the cluster heads will be responsible for assigning particular slots to members. | (i) The future work may include the extension towards simulating the system in other simulation platforms such as NS3 and then assessing the system performance.<br>(ii) The future research direction also considers other energy sources such as vibration or pressure and comparing our framework with MAC protocols other than LEACH. |
| | Sommer et al. [71] | State of charge for battery | (i) This article presents a framework for estimating the state of charge for a battery of sensor node by considering the two points (1) the current flow in the battery and (2) the battery voltage is used as a measure of absolute state of charge.<br>(ii) Further, this article shows that appropriate prediction of the state of charge can be used for adaptively scheduling for operations having energy-neutral characteristics for multiple applications of sensor nodes. | (i) The future research direction may include efforts towards improving the prediction efficiency by incorporating some advanced methods such as recurrent neural networks or other alternatives. |
| | Li et al. [72] | Consumption of energy and time | (i) This article proposes a scheme for the scheduling of the dynamic reconfiguration for a sensor node.<br>(ii) Further, this scheduling framework considers various factors such as statistical information on tasks and | (i) The future work will explore other communication mechanisms that will be more energy-efficient in an energy harvesting environment. |

Table 2: Continued.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | | | available energy under an energy harvesting environment. | |
| 2014 | Chetto [73] | Energy and time constraints | (i) This article proposes a semionline scheduling algorithm that is based on the earliest deadline first methodology.<br>(ii) Further, this framework depends on two specific factors such as energy demand and slack energy. | (i) The future work may include an extension towards incorporating fixed priority environments in the proposed framework.<br>(ii) Next, extension towards supporting dynamic voltage and frequency selection technology.<br>(iii) Furthermore, the extension towards considering the smallest harvester etc. |
| | Castagnetti [74] | Packet reception ratio & energy efficiency | (i) This article proposes the power management framework for EH-WSNs.<br>(ii) Next, the proposed framework utilized two factors, namely, optimization of duty cycle and power control in transmission. | (i) The future work may include extension towards considering various adaptation methodologies, namely, adaptive modulation and coding for improving the performance and energy efficiency. |
| | Li et al. [75] | Total number of executed tasks | (i) This article proposes the task scheduling scheme utilizing prediction data, and further, this framework is based on weather forecasts in EH-WSNs. | (i) The future work may include extension towards exploring the advantages of weather forecasting data for longer scheduling. |
| 2015 | Liu et al. [76] | Energy utilization & deadline miss rate (DMR) | (i) In this article, an intratask scheduling scheme is presented for the storage-less and converter-less channels.<br>(ii) Next, this framework utilizes neural network training. | (i) The future work may include extension towards utilizing the learning automata in place of the neural network and then assessing the system performance. |
| | Zhang et al. [77] | Total number of ready tasks & deadline miss rate (DMR) | (i) This article proposes the scheduling algorithm utilizing the neural network for determining the appropriate scheduling pattern, the optimal size of the capacitor, and finally queue of tasks for improving the deadline miss rate. | (i) The future work may include extension towards utilizing other alternatives in place of ANN such as learning automata for further enhancing the deadline miss rate. |
| 2016 | Ali [78] | Lifetime of battery & consumption of power | (i) This article proposes the event-driven duty cycling framework for reducing the power consumption of the roadside unit which are having self-powered capabilities. | (i) The future work may include extension towards modifying the proposed framework by including few more factors, such as the weather conditions, for enhancing the performance of the distributed power management scheme. |
| | Gomez et al. [79] | Efficiency of system | (i) This article proposes an efficient energy management unit to maintain power supply especially in those circumstances in which the harvested power is not sufficient for smooth system operation. | (i) In the proposed work, optimal-sized buffer is used and the future work may include the variable-sized buffer and then measuring the system efficiency. |
| | Zhang et al. [80] | Efficiency in energy utilization & deadline miss ratio (DMR) | (i) This article proposes a new scheduling framework.<br>(ii) Next, this framework consists of various key attributes such as power prediction, task priorities are defined | (i) The future work may include extension towards exploring the scheduling framework with different energy sources such as thermal, |

Table 2: Continued.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | | | by using an artificial neural network, and finally an algorithm for selecting the task. | wireless, and vibration and also some hybrid approaches. |
| | Oueis et al. [81] | Harvested energy, battery residual energy, and battery level variation | (i) This article discusses the effect of photovoltaic energy harvesting on the duty cycle of sensor nodes in both scenarios outdoor and indoor. | (i) The future work may include extension towards evaluating and comparing several other performance metrics such as end-to-end delay and packet delivery ratio. |
| | Housseyni et al. [82] | Success ratio for deadline | (i) This article proposes a new scheduling framework for a sporadic task model.<br>(ii) Next, an energy-efficient offline task assignment heuristic is generated by the proposed framework. | (i) The future work may include an extension towards exploring the proposed framework in which arrival times are characterized with probabilistic distributions. |
| | Maeda et al. [83] | End-to-end delay, total number of packets sent to base station (sink) per cycle, and the fairness index for the node position | (i) This article proposes a task scheduling scheme in which data is periodically collected from the sensor nodes. | (i) In this article, line topology is used for simulating the sensor network and future work may include extension towards adopting other topology and then measuring the performance of the system. |
| 2017 | Sanchez et al. [84] | Final remaining energy of sensor node | (i) The energy management strategy is based on a hybrid dynamical system approach.<br>(ii) The combination of continuous physical processes results in the hybrid nature; on the other hand, change in the functioning modes results in the discrete concept. | (i) In the current work, the sensor nodes' energy is modeled using a specific representation named as a hybrid dynamical systems representation; future work may include modeling the energy with other representations and then measuring the performance. |
| 2018 | Huang et al. [85] | Optimal expected rewards | (i) This article proposes a scheduling policy for EH-WSNs based on the threshold value.<br>(ii) In this framework, limited memory is needed for storing optimal threshold values at the sensor node for carrying out energy management activity. | (i) The future work may include an extension towards utilizing Markov channels for energy harvesting systems.<br>(ii) In this scenario, the system state will be represented by data packets, energy, and the state of the wireless channel. |
| | Bengheni et al. [86] | Mean latency, throughput, and packet delivery ratio (PDR) | (i) This article proposes the enhanced energy management scheme in EH-WSNs.<br>(ii) Further, this framework utilizes receiver-initiated communication.<br>(iii) Next, a policy based on the energy threshold is used for controlling the active/sleep periods. | (i) Future work may include extension towards considering other performance metrics such as average energy consumption and network lifetime. |
| | Anagnostou et al. [87] | Rate of execution and energy efficiency | (i) This article proposes a hardware scheduling framework that is power-aware.<br>(ii) Next, this framework also observes harvesting power.<br>(iii) Further, the available energy along with the software module is used to dynamically activating the other system modules. | (i) Future work may include extension towards using the dynamic schedulers and also supporting the interruptible tasks. |
| | Galmés and Escolar [88] | Energy consumption | (i) This article discusses solar energy harvesting-based WSN for monitoring | (i) Future work may include extension towards using other software (with |

Table 2: Continued.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | | | the environment.<br>(ii) In this article, an analytical approach is used for enforcing the duty cycle. | corresponding hardware) platforms.<br>(ii) Next, geographic latitude and meteorological conditions of the deployment should be used for refining the energy harvesting model. |
| | Cui [89] | Mean relative error, and root mean square error | (i) This article proposes the solar energy prediction method which is based on long short-term memory recurrent neural network.<br>(ii) Also, a predictive task scheduling framework is proposed based on the prediction of energy available for improving the overall performance of the WSN. | (i) Future work may include extension towards using other alternatives in prediction such as gated recurrent unit (GRU) and bidirectional LSTM (bi-LSTM) and then measuring the performance. |
| 2019 | Sommer et al. [90] | Average tracking error | (i) In this article, a scheduling framework is presented which is having awareness about energy and mobility for achieving long-term tracking.<br>(ii) This framework calculates the virtual energy budget for forecasting energy. | (i) The future work may include extension towards incorporating some more advanced algorithms or some hybrid approach consisting of several methods for efficiently predicting energy harvesting. |
| 2020 | Zhang et al. [91] | Common active time (CAT) | (i) This article discusses the stochastic duty cycling problem and studies it under three cases (offline, online, and correlated stochastic duty cycling) to maximize utilization efficiency. Also, an offline algorithm is designed for the offline case with optimal performance. | (i) The point-to-point model can be extended to the networked case, such as multihop networks, where each device may have more than one neighbor. In multihop networks, the different pairs of neighboring nodes can be assigned with different periods by the coloring technique. |

framework can handle real-time traffic efficiently by providing optimal routes.

*4.7. Schemes Based on Optimization of Power for the Hardware Devices.* Schemes based on optimization of power can be further classified into two categories such as processor power management and device management. A brief discussion about these schemes is provided below.

The rapid development in the IC fabrication technology and current innovations in semiconductor technology results in a tremendous transformation in the field of high-performance computing such as starting from the development of single-core architecture to multicore architecture with homogeneous characteristics and then multicore architecture with heterogeneous and dynamic reconfigurable characteristics. This rapid development further imposes a challenge in terms of increment in power density as well as heat dissipation and consequently affected the system reliability and availability. Currently, research is going on achieving high performance with low power consumption. Nagalakshmi and Gomathi [96] have presented various effective techniques for overall reducing the power dissipation in multicore processing architecture. Further, there is an urgent need to handle power management issues for designing efficient microprocessors in current scenarios of high-performance computing. The ultimate goal is to maximize the performance of the processor with low power consumption. The role of power management techniques is to maintain the balance between higher performance and power consumption with aggressive thermal effects. Next, Attia et al. [97] have explored the various schemes for managing the power in multicore processing architecture.

The designing of an electronic system should be harvesting-aware from two perspectives such as the hardware and software perspectives for achieving optimal performance in the energy harvesting environment. Also, the efficiency of the harvesting system can be enhanced by utilizing a proper power management framework with harvesting-aware characteristics. Further, an efficient power management framework will enable the harvesting system to operate uninterruptedly and achieve the expected objectives. One of the prominent operating modes is the energy-neutral mode that can provide assurance about longer system operation [98]. Further, an efficient and proper functional power management framework is the need of the hour in the current high-performance demanding environments for an energy harvesting device. The harvested energy is stored in the energy storage element until enough energy is currently available to enable the sensor nodes to complete the desired task [99].

*4.8. Schemes Based on Optimization of Communication Mechanism.* Schemes based on optimization of communication mechanism can be further classified into three major categories, namely, MAC protocols for EH-WSNs, transmission schemes classification, and also routing protocols for EH-WSNs. A brief discussion about all these schemes is provided below.

*4.8.1. MAC Protocols for EH-WSNs.* These are further categorized into three categories such as sender-initiated asynchronous protocols, receiver-initiated asynchronous protocols, and also sink-initiated asynchronous protocols. Tables 3–5 are used to briefly describe each respective category clearly as follows.

*(1) Sender-Initiated Asynchronous Protocols*. Three MAC protocols are described in this category in Table 3, and these include EL-MAC [100], RF-MAC [101], and also DeepSleep [102].

*(2) Receiver-Initiated Asynchronous Protocols*. Six MAC protocols are described in this category in Table 4, and these include ODMAC [103], EH-MAC [104], QAEE-MAC [105], ERI-MAC [106], LEB-MAC [92], and also ED-CR and ED-PIR MAC [107].

*(3) Sink-Initiated Asynchronous Protocols*. Four MAC protocols are described in this category in Table 5, and these include PP-MAC [108], MTPP-MAC [109], RF-AASP [110], and also AH-MAC [111].

*4.8.2. Transmission Schemes Classification.* Transmission schemes are divided into three categories, namely, fixed transmission schemes, variable transmission schemes, and also probability model-based transmission schemes. These schemes are briefly described below.

*(1) Fixed Transmission Schemes*. Reddy and Murthy [112] have effectively addressed the power management issue in EH-WSNs. They have proposed the framework that is based on the approach of energy-neutral for managing the power efficiency issues in communication and therefore enhancing the utility of sensor nodes that are utilizing the harvested energy. The designing of this framework clearly incorporates three factors such as fixed power consumption in the circuits, inefficiencies of battery, and finally storage capacity.

*(2) Variable Transmission Schemes*. The energy harvesting mechanism is considered as the prominent solution for sustained WSNs. In EH-WSNs, two important factors need to be considered while designing the optimal transmission policies such as the mechanism of energy refreshing and the storage constraints for rechargeable batteries. Tutuncuoglu and Yener [113] have tried to address these issues with optimum solutions. The proposed framework specifically tried to determine the transmission policy that enhances the data transmission rate in a bounded timeline. Finally, the proposed framework determined the optimum transmission policies with constraints such as the mechanism of energy refreshing and the storage constraints for rechargeable batteries. The mechanism of energy refreshing considers the model having discrete packets for energy arrivals. Next, the energy harvesting technique usually suffers from two vibrant issues such as instability and random behavior in harvested energy and these two issues need to be tackled efficiently since these issues cause temporal death of sensor nodes and thereby making a negative impact on the quality of service and overall performance starts degrading. Tang and Tan [114] have proposed the framework which considers the case of temporal death and analyzes the behavior of energy harvesting devices for data transmission characteristics, and further, the proposed framework determines the optimal transmission policy.

*(3) Probability Model-Based Transmission Schemes*. Berbakov et al. [115] have presented the approach for determining the optimal joint transmission scheme in a particular scenario consisting of two sensor nodes in which one is battery operated and another one is operated purely based on the harvested energy. Also, in this framework, the common message is transmitted to the base station cooperatively. The ultimate aim is to find the optimal joint transmission scheme for maximizing the throughput with the bounded deadline. Next, Michelusi et al. [116] have proposed an approach for handling the issue of uncertainty in estimating the state of charge for rechargeable batteries since it is almost impractical or very costly to accurately estimate the state of charge for the rechargeable battery. Also, the proposed approach noted the impact of deficient information about the state of charge on WSNs.

*4.8.3. Routing Protocols for EH-WSNs.* The energy scarcity issue of sensor nodes is an evergreen research area for both traditional WSNs and also for EH-WSNs. In the case of traditional WSNs, sensor nodes operated with limited capacity battery usually start struggling for providing optimum performance after specified time duration, and as a result, the performance of the network starts degrading, and there is a need for efficient utilization and management of harvested energy in case of EH-WSNs. Therefore, the energy issue is considered as a primary factor in designing routing protocols for both traditional WSNs and for EH-WSNs. Further, routing protocols for EH-WSNs are divided into four major categories, namely, routing protocols based on the cost of routes, based on passive characteristics, based on geographic area, and also based on clustering. These are briefly described as follows.

*(1) Routing Protocols Based on Cost of Routes*. Pais et al. [117] have presented a newly designed function reflecting cost-benefit for EH-WSNs. Their research work consists of the main innovation in terms of a new routing cost metric. Further, this routing cost metric is utilized for prolonging the lifetime of the sensor network. Next, Martinez et al. [118] have proposed an efficient framework for selecting the routes.

Table 3: Sender-initiated asynchronous protocols.

| Year | Author and reference details | Proposed MAC protocol | Metric used for evaluating the performance | Hops count | Bullet points | Future research directions |
|---|---|---|---|---|---|---|
| 2014 | Kim et al. [100] | EL-MAC | Throughput, and energy efficiency | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as MAC protocol with consideration of the different levels of energy.<br>(ii) The energy efficiency as well as higher throughput has been ensured in the proposed framework.<br>(iii) The proposed framework also provides a strategy for efficient sensing by giving the highest priority to users having a lower energy level for ensuring the communication opportunity. | (i) Future research directions may consider the work towards the evaluation of the proposed scheme under different energy harvesting environments. |
| | Naderi et al. [101] | RF-MAC | Harvested energy and throughput | Multihop | (i) A new MAC protocol has been presented for EH-WSNs which is known as radiofrequency energy transferring MAC.<br>(ii) The proposed MAC protocol is optimizing the sensor node's energy delivery.<br>(iii) The proposed framework reduces the disruption in the communication mechanism. | (i) Future research directions may consider the work towards enhancing the optimization of spectrum selection mechanism by using some advanced efficient optimization technique. |
| 2015 | Lin et al. [102] | DeepSleep | Energy efficiency, application layer loss rate, and outage probability | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as DeepSleep MAC.<br>(ii) The proposed MAC protocol is significantly reducing the collision probability, outage probability, and also application layer loss rate; on the other hand, energy efficiency has been increased.<br>(iii) The proposed framework considered fairness in the access mechanism during the design step. | (i) Future research directions may consider the work towards formulation of complex optimization problem concerning to relationship among multiple parameters which are part of the proposed framework.<br>(ii) Next, multiple sleep probability values may be considered for applying to various devices for guaranteeing the packet delay time.<br>(iii) Further, the energy harvesting 802.11ah devices may be explored for analyzing the design space. |

Special emphasis has been given to the amount of the wastage of network energy which is generally not considered in the previous literature while selecting the appropriate routes. The main source of this network energy wastage is due to overcharging of limited capacity batteries in the network, and this is the main innovation in this framework. Therefore, this framework achieves higher levels of residual energy by reducing energy consumption.

*(2) Routing Protocols Based on Passive Characteristics*. The routing protocols based on passive characteristics utilize the past information about the network and do not actively consider the current state of the network for constructing the routing tables. Further, Kollias and Nikolaidis [119] have implemented a seasonally aware routing protocol. In this routing protocol, two factors are considered for the construction of routing tables such as solar energy harvesting rates and information about the several routes created in the past years. These passively attributed routing protocols are having an advantage in the specific scenario in which they reduce the wastage of energy in routes establishment overhead in the network, but on the other side, if a particular sensor node dies, then these protocols unable to recover it due to their passive nature.

*(3) Routing Protocols Based on Geographic Area*. Jumira et al. [120] have proposed an efficient geographic routing scheme for EH-WSNs. The salient features of this energy-efficient beaconless geographic routing consist of loop-free nature with minimum communication overhead and stateless, and also, this routing does not require any prior knowledge about the neighborhood for communication. Further, the mechanism of this routing framework is different from other geographic routing and it started by first sending the data

Table 4: Receiver-initiated asynchronous protocols.

| Year | Author and reference details | Proposed MAC protocol | Metric used for evaluating the performance | Hops count | Bullet points | Future research directions |
|---|---|---|---|---|---|---|
| 2011 | Fafoutis and Dragoni [103] | ODMAC | Ratio of harvested energy and consumed energy, average delay, average sensing period, and load balancing | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as on-demand MAC. (ii) The proposed MAC protocol is capable to support a separate duty cycle for sensor nodes having different energy levels. | (i) Future research directions may consider the work towards using the retransmission mechanism and further consideration of the lossy environment for its evaluation. (ii) Next, future research directions may consider the work towards handling hidden node problems by utilizing the CTS/RTS scheme. |
| 2012 | Eu and Tan [104] | EH-MAC | Network capacity, fairness, and throughput | Multihop | (i) A new MAC protocol has been presented for EH-WSNs which is known as EH-MAC. (ii) The proposed MAC protocol has utilized probabilistic polling for reducing the collisions among data packets. (iii) Also, in the proposed framework, polling packets are dynamically adjusted for reducing interference. | (i) Future research directions may consider the extension towards using an advanced scheme for energy management with some smart scheme for collision resolution among the packets. |
| | Kim et al. [105] | QAEE-MAC | Delay and total energy saving | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as quality-of-service-aware energy-efficient priority-based MAC. (ii) The receiver node's energy consumption has been significantly minimized by adjusting its wake-up duration as per the energy profile. | (i) Future research directions may consider the extension towards using some advanced metric for duty cycle evaluation such as the expected number of duty cycle wake-ups and using the concept of the dynamic and heterogeneous duty cycle. |
| 2014 | Nguyen et al. [106] | ERI-MAC | Delivery latency and energy efficiency | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as energy-harvested receiver-initiated MAC. (ii) The proposed framework utilized the queueing scheme for adjusting the sensor node operation. | (i) Future research directions may consider the extension towards using various harvesting models and then analyzing the effects on ERI-MAC. (ii) Next, future research directions may consider the work towards extending the packet concatenation scheme. |
| | Liu et al. [92] | LEB-MAC | End-to-end delay, sender duty cycle, delivery ratio, collision ratio, and fairness index | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as load and energy balancing MAC. (ii) The proposed scheme utilized the fuzzy control technique for determining the duty cycles of sensor nodes. | (i) Future research directions may consider the extension towards using other techniques for determining the duty cycles of sensor nodes such as probabilistic controller, approximation algorithm, and nonlinear function controller in place of fuzzy control technique. |
| | Varghese Rao [107] | ED-CR MAC & ED-PIR MAC | End-to-end delay, energy consumption, and packet delivery ratio | Multihop | (i) Two new MAC protocols have been presented for EH-WSNs. The first MAC scheme utilized exponential decision along with the current state of residual energy | (i) Future research directions may consider the extension towards using some other advanced approaches for duty cycle adjustment and then measuring |

Table 4: Continued.

| Year | Author and reference details | Proposed MAC protocol | Metric used for evaluating the performance | Hops count | Bullet points | Future research directions |
|---|---|---|---|---|---|---|
| | | | | | and the second scheme utilized exponential decision along with increment in residual energy prospectively.<br>(ii) The first proposed scheme utilized the dynamic approach with consideration of the current state of residual energy for duty cycle adjustment step. Further, the second proposed scheme attains energy efficiency by minimizing the duty cycle off time. | the performance under different harvesting models. |

Table 5: Sink-initiated asynchronous protocols.

| Year | Author and reference details | Proposed MAC protocol | Metric used for evaluating the performance | Hops count | Bullet points | Future research directions |
|---|---|---|---|---|---|---|
| 2011 | Eu et al. [108] | PP-MAC | Throughput, fairness, and interarrival times | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as probabilistic polling MAC.<br>(ii) The proposed framework considers the unpredictable behavior of the energy harvesting mechanism for achieving optimal performance. | (i) Future research directions may consider the work towards developing and evaluating the MAC protocol for multihop scenarios. |
| | Fujii and Seah [109] | MTPP-MAC | Scalability, throughput, and fairness | Multihop | (i) A new MAC protocol has been presented for EH-WSNs which is known as multitier probabilistic polling MAC.<br>(ii) The proposed framework utilizes the multitier probabilistic polling scheme for optimal delivery of data in EH-WSNs. | (i) Future research directions may consider the work towards considering other energy harvesting environments since the current proposed scheme utilizes the solar energy harvesting environment. |
| 2016 | Nguyen et al. [110] | RF-AASP | Energy efficiency, delay, and throughput | Single hop | (i) A new MAC protocol has been presented for EH-WSNs which is known as RF-adaptive active sleep period MAC.<br>(ii) The proposed framework reduces the network contention level and enhances the harvested energy thereby achieving energy efficiency. | (i) Future research directions may consider the work towards considering other energy harvesting environments since the current proposed scheme utilizes the RF energy harvesting environment. |
| 2017 | Al-Sulaifanie et al. [111] | AH-MAC | Energy consumption, nodes alive, delivery ratio, and normalized performance metrics | Multihop | (i) A new MAC protocol has been presented for EH-WSNs which is known as adaptive hierarchical MAC.<br>(ii) The proposed framework utilizes the cross-layer optimization for dense and low rate WSN. | (i) Future research directions may consider the work towards considering other energy harvesting environments since the current proposed scheme utilizes the solar energy harvesting environment. |

packet in place of sending the usual control messages which is a general trend in geographic routing. Next, only those neighbors are selected for communication that initially received the data packet successfully and, in this way, appropriate neighbors are selected for efficient communication. Next, Hieu and Kim [121] have proposed a unique geographic routing scheme for EH-WSNs. In this routing framework, four parameters are considered for selecting the appropriate routes, namely, quality of link, residual energy, location information, and also energy harvesting rate. The ultimate aim of this geographic routing is to select reliable routes and thereby enhancing the lifetime of the network. Further, the detailed review of opportunistic routing utilizing the concept of geographic characteristics is provided in Table 6.

*(4) Routing Protocols Based on Clustering.* The clustering mechanism significantly contributes towards energy efficiency in EH-WSNs.

A detailed review of clustering-based routing is provided in Table 7.

*4.9. Schemes Based on Optimization of Battery Operation.* In this section, the main focus is on the issue of efficiently managing the operations of sensor nodes. The brief discussion is provided as follows.

In EH-WSNs, the currently available energy profile is considered for the transmission of data packets; these data packets are generated by the sensor nodes after periodically sensing the field and further stored in the queue. Sharma et al. [144] have presented the optimal energy management schemes for sensor nodes having energy harvesting capabilities. Further, these schemes are attributed as optimal throughput and mean delay. The proposed schemes are aimed at achieving the energy-neutral operation condition in the network. Further, Sinha and Chandrakasan [145] have proposed a scheme for enhancing the energy efficiency of nodes which is actually a power management scheme based on the microoperating system. Next, Chetto and Ghor [146] have analyzed the energy harvesting system having dynamic power management capabilities for selecting the appropriate scheduler on a uniprocessor platform with applicative conditions.

*4.10. Mobility-Based Schemes.* The mobility-based schemes are further classified into two categories, namely, mobile relay-based and also mobile sink-based schemes. A brief discussion about these schemes is provided below.

The mobility-enabled WSNs are suffering from higher latency factors in specific activities towards the collection of data. The mobile base stations are generally moving at a slower speed for collecting the data which further results in increasing the latency. This issue severely degrades the performance of mobility-enabled WSNs. Researchers explore the issue and find that energy efficiency can be achieved by resolving this issue. Xing et al. [147] have proposed a scheme and tried to address this issue with efficiency. The proposed scheme makes a significant contribution towards balancing the two factors such as energy efficiency and latency factor in the mobility-enabled WSNs. In the proposed scheme, few sensor nodes buffer and aggregate the data and play the role of rendezvous points for the base station for the collection of data.

Next, another challenging issue arises due to the fact that data should be transmitted to the base station only during the lifetime of the particular application. This requirement is hard to achieve in the environment of bounded supplies of power. Moukaddem et al. [148] have proposed a scheme and tried to resolve this issue by introducing the concept of mobile relays and thereby reducing the energy consumption in data-rich WSNs.

In WSNs, the energy holes issue can be resolved by using the concept of sink mobility. The sink mobility scheme efficiently balances the energy and consequently handles the energy hole issue. In the sink mobility scheme, sensor nodes consume less energy since data collection activities occurred in a single hop by the mobile sink which is generally moving throughout the network. In the sink mobility environment, one major issue arises in data forwarding to mobile sink only during time-bound emergency circumstances, and in these situations, sensed data start losing its relevance in the bounded course of time; this sensitive issue needs to be resolved carefully. Ghosh et al. [149] have proposed an efficient scheme in which the Moore curve trajectory motion is used by the mobile sink for the collection of data. The other salient features including any forwarding and also strict sleep/wake-up policy have been followed for sensor nodes.

Next, for specific applications, the unpredictable movement behavior of the mobile sink causes performance degradation since the source sensors tried to locate the continuous moving mobile sink before actual reporting of data. The ultimate aim is to use the minimum number of hops for sending the data to a continuous moving mobile sink and the reason is obvious with the minimum number of hops leads to energy efficiency. Cheng et al. [150] have proposed the framework that addresses both the concerns such as locating the mobile sink efficiently and also reducing hops count.

*4.11. Energy Balancing Schemes.* The tiny sensor nodes collect the information for the specific event, and further, this information is transmitted to the sink; this is considered as the basic mechanism of WSNs. But, the transmission range issue creates hurdles in monitoring the large area in WSNs and now the need for relay nodes arises further with the help of relay nodes information reached to the sink node. Again, this step creates an imbalance in traffic share which results in an imbalance in energy consumption. The imbalance of energy also results in variation in the lifetime of sensor nodes. The reason is clear as some relay nodes are highly occupied with a portion of traffic and therefore consume a high amount of energy and soon they become dead. Dead nodes cause network portioning and thereby collected information unable to reach the destination, and the basic objective cannot be attained. Now all these circumstances force us to think about the need for an energy balance framework in WSNs. The energy balancing framework efficiently manages the traffic load in WSNs and therefore balances the lifetime of sensor

Table 6: Review of various opportunistic routing schemes considering the geographic characteristics.

| Year | Author and reference details | Proposed opportunistic routing framework | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|---|
| 2010 | Eu et al. [122] | EHOR | Fairness, hop count, efficiency, data delivery ratio, goodput, throughput, and source sending rate | (i) An opportunistic routing framework is proposed with consideration of energy constraints for multihop EH-WSNs. | (i) As future work, the proposed framework can be used for a 2D topology.<br>(ii) Next, future work includes the use of network coding for enhancement of performance. |
| 2012 | Eu and Tan [123] | AOR | Throughput and fairness | (i) An adaptive opportunistic routing framework is proposed for multihop EH-WSNs.<br>(ii) The proposed framework provides a higher throughput.<br>(iii) The proposed framework utilized the regioning scheme and also capable enough to change as per conditions of network and energy profiles. | (i) Future research directions may consider the work towards addressing factors that are not addressed in this framework.<br>(ii) The cost of multihop transmission is affected by the duty cycle of relay nodes and it results in the selection of inappropriate routes. |
| 2013 | Beheshtiha et al. [124] | OR-AhaD | Hop count, data delivery ratio, goodput, and efficiency | (i) An opportunistic routing framework is presented with a duty cycle approach having awareness of adaptive harvesting mechanism.<br>(ii) The proposed framework utilized the geographical zoning approach for prioritizing the candidates set.<br>(iii) The model is presented for managing the energy, and in this model, the duty cycle is adaptively adjusted based on the estimation of harvesting rate in the future. | (i) Future research directions may consider the work towards consideration of the effect of prediction accuracy in the performance of the routing framework.<br>(ii) Next, future research directions may consider the work for the requirement of the unified evaluation framework for comparing the existing solutions.<br>(iii) Further, future research directions may consider the work towards test-bedding the existing routing frameworks for exploring the implementation issues. |
| 2017 | Shafieirad et al. [125] | Max-SNR | Data delivery ratio and transmitted messages per node | (i) A novel opportunistic routing framework is presented for multihop large-scale EH-WSNs with energy awareness.<br>(ii) The proposed scheme considered the three factors while selecting the next forwarder such as energy profile, distance, and also the amount of data. | (i) Future research directions may consider the work towards addressing factors that are not addressed in this framework.<br>(ii) The proposed scheme may result in packet loss as well as poor delay in the case of heterogeneous and dynamic duty cycle and consequently selecting the sleeping relay nodes for packet transmission.<br>(iii) The duty cycle cannot be adjusted accurately and this results in the limited performance of EH-WSNs. |
| 2018 | Zhang et al. [126] | OPEH | Delivery ratio and delay | (i) A novel opportunistic packet forwarding framework is presented with consideration of heterogeneous and dynamic duty cycle.<br>(ii) The echo state network is utilized for adjusting the duty cycle. | (i) Future research directions may consider the work towards enhancing the efficiency of the echo state network since it is utilized in the current work for adjusting the duty cycle. |
| 2019 | Cheng et al.[127] | ORDTP | Packet redundancy ratio, delay, and delivery ratio | (i) An opportunistic routing framework is presented with | (i) Further, future research directions may consider the work |

Table 6: Continued.

| Year | Author and reference details | Proposed opportunistic routing framework | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|---|
| | | | | consideration of dynamic transmission power for EH-WSNs. (ii) The salient features of the proposed framework include collecting the information about neighbor nodes and estimation of the transmission cost accurately. (iii) In the proposed framework, the priorities, members, and size are dynamically updated. | towards test-bedding the existing routing framework for exploring the performance in actual deployment with implementation issues. |
| 2020 | Rathore et al. [128] | OOR | Delay, packet delivery ratio, and throughput | (i) An optimal opportunistic routing framework is presented with consideration of a dynamic duty cycle based on the modified echo state network for EH-WSNs. (ii) In the proposed framework, the whale optimization algorithm is used for enhancing the prediction efficiency of the echo state network. | (i) Further, future research directions may consider the work towards test-bedding the existing routing framework for exploring the performance in actual deployment with implementation issues. |
| 2020 | Singh and Pattanayak [129] | MEHOR | Efficiency, throughput, goodput, source sending rate, data delivery ratio, and hop counts | (i) An opportunistic routing framework is presented with consideration of cross-layer design. (ii) The proposed framework utilized the Markovian model for cross-layer design. | (i) Further, future research directions may consider the work towards key challenges in the proposed framework such as reducing the duplicate packets. |

nodes. The aim is to improve the lifetime of WSNs and to try to maintain the ideal environment in which all sensor nodes share the same lifetime with no variation. But in multihop WSNs, this condition is not feasible to maintain since the traffic density is increased near the sink. Therefore, in multihop WSNs, the objective is to balance the energy consumption.

A detailed review of energy balancing schemes is provided in Table 8.

## 5. Challenges in EH-WSNs for Formulating Optimization Problems along with Solutions

EH-WSNs are having various challenging issues which are further formulated as optimization problems. These multiobjective optimization problems can be solved by utilizing various efficient optimization algorithms that are currently available. A detailed classification of various existing challenges for green WSNs is illustrated in Figure 11.

Next, with the help of another (Figure 12), we are trying to illustrate some key challenges in EH-WSNs for formulating optimization problems along with algorithms for providing the solution to optimization problems in EH-WSNs. Therefore, Figure 12 is having two blocks; further, in the first block, some key challenges are represented, and in the second block, algorithms are depicted for providing the solution to multiobjective optimization problems. In the following section, we are trying to address challenges as well as solutions in detail.

In [166], two important metrics such as aggregate utility and network lifetime are considered for performance evaluation. Further, to achieve enhanced network lifetime along with improved aggregate utility, a multiobjective stochastic algorithm is utilized. There exist a large number of real-life optimization problems in different fields, and the optimal solutions of these optimization problems require specially designed optimization models along with the algorithms having multiobjective computational solution capabilities with stochastic nature.

Further, in WSNs, the sensor node is having limited capabilities in processing the particular event and therefore a single node would require high processing energy to solve the particular problem and the only solution in these circumstances is the distributed approach. In the distributed framework, the part of the solution concerning the particular node is required to be sent to the respective nodes. The overall communication overhead in the distributed approach is less as compared to a centralized approach since in the centralized approach, transmission mechanism occurs from the sensor node (solving) to all the other nodes as compared to the distributed approach in which the transmission mechanism occurs to a subset of nodes [167]. Further, in [168], for determining the trade-off between enhanced network lifetime and QoS, a multiobjective routing framework is

Table 7: A detailed review of clustering-based routing.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| 2012 | Meng et al. [130] | Number of nodes available and throughput | (i) A new clustering routing protocol is presented for EH-WSNs which is known as an adaptive energy harvesting-aware clustering routing protocol.<br>(ii) In the proposed framework, energy state of the node is considered for selecting the cluster head.<br>(iii) The parameters in the proposed framework can be adjusted as per the deployed environment. | (i) Future research directions may consider the work towards some more advanced energy-efficient schemes with more metrics for cluster head elections. |
| 2013 | Xiao et al. [131] | Throughput, number of dead nodes, and data failure rate | (i) A new function has been proposed which is known as the energy potential function for assessing the capabilities of sensor nodes in terms of harvested energy.<br>(ii) Next, for EH-WSNs, a new protocol known as energy potential LEACH has been presented which is the extended version of the LEACH. | (i) Future research directions may consider the work towards applying the proposed framework in the practical environment with consideration of two constraints related to sensor nodes such as the capacity of the battery and limited computing capabilities. |
| | Zhang et al. [132] | Number of rounds until the first node dies | (i) A new framework has been proposed for enhancing the lifespan of the network.<br>(ii) In the proposed framework, the relay nodes for cluster heads are actually the energy harvesting sensor nodes. | (i) Future research directions may consider the work towards proposing a new distributed EH clustering scheme.<br>(ii) The next work may be related to exploring energy harvesting nodes with different configurations.<br>(iii) The next work may be related to using the testbed for evaluating the proposed framework. |
| 2014 | Mostafa and Hassan [133] | Number of alive nodes | (i) A new clustering algorithm has been presented for EH-WSNs in which three factors are considered primarily such as sensor node centrality, amount of energy harvested, and the total neighbors.<br>(ii) Next, fuzzy petri nets are used in the proposed algorithm for selecting the cluster heads. | (i) Future research directions may consider the work towards using type-2 fuzzy petri nets and other advanced versions such as extended TOPSIS for selecting the cluster heads. |
| 2015 | Peng et al. [134] | Accumulated cluster failure time and total amount of information bits | (i) A new framework has been proposed for clustering in EH-WSNs and is known as the distributive energy-neutral clustering protocol.<br>(ii) The proposed framework utilizes the novel cluster head group mechanism.<br>(iii) Next, for efficiently handling the high traffic load, a cluster is allowed to use multiple cluster heads. | (i) Future research directions may consider the work towards using hybrid advanced metaheuristic algorithms for finding the solution to the optimization problem in terms of the optimal number of clusters. |
| | Yukun et al. [135] | Total number of cluster heads, alive nodes, success ratio of data transmission, and residual energy | (i) A new clustering routing framework has been presented for solar energy-harvested WSNs.<br>(ii) The proposed framework utilized the energy threshold factor for reviving the sensor nodes. | (i) Future research directions may consider the work towards using other energy harvesting environments since the proposed framework dedicated to solar energy harvesting. |
| | Li and Liu [136] | Normalized average throughput, awake nodes, and residual energy | (i) A new clustering routing framework has been presented for EH-WSNs.<br>(ii) The proposed framework utilized discrete particle swarm optimization. | (i) Future research directions may consider the work towards optimization of the sensor nodes number in each cluster.<br>(ii) Next, the future work may consider two |

Table 7: Continued.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | | | (iii) Next, in the proposed framework, the modified discrete particle swarm optimization algorithm has been utilized for determining the optimal topology. | performance metrics, namely, throughput and alive nodes for comparing the proposed framework with the distributed framework. |
| 2016 | Li and Liu [137] | Normalized average throughput, awake nodes, and residual energy | (i) A new distributed clustering routing framework is presented for EH-WSNs.<br>(ii) In the proposed framework, the cluster head electing mechanism is based on the current residual energy profile of the sensor nodes and the amount of harvested energy.<br>(iii) Also, the proposed framework utilized the model for predicting solar energy based on a neural network. | (i) Future research directions may consider the work towards dynamic tuning of various coefficients that are used in the framework for overall improving the performance.<br>(ii) The next future work may consider other different prediction models for solar energy for improved accuracy. |
| 2017 | Bozorgi et al. [138] | Alive nodes and average energy of alive nodes | (i) A new hybrid framework has been proposed consisting of both static and dynamic clustering mechanisms.<br>(ii) The distributed-centralized approach with multihop routing has been used in the proposed framework.<br>(iii) The proposed framework considers the three primary factors for the clustering mechanism such as the current level of energy, the number of neighbors, and the amount of harvested energy. | (i) Future research directions may consider the work towards some more advanced energy-efficient schemes with more metrics for cluster head elections in the clustering mechanism. |
| 2019 | Afsar and Younis [139] | Live nodes, throughput, consumed energy, and maximum hop count | (i) A new cross-layer design framework has been presented with capabilities such as energy scavenging and transfer for EH-WSNs.<br>(ii) The proposed framework adopted a distributed two-tier routing topology.<br>(iii) The proposed framework divided the network into virtual tracks further the width is based on the density of node and distance to the base station. | (i) Future research directions may consider the work towards some more advanced energy-efficient schemes with more metrics for cluster head elections in the clustering mechanism. |
| 2020 | Ge et al. [140] | Packets received by the base station, packets received by the cluster head, and failure node ratio | (i) A new uneven clustering framework has been presented for EH-WSNs.<br>(ii) In the proposed framework, the energy prediction model is based on a long short-term memory.<br>(iii) Also, the proposed framework considers the energy consumption of the node with supplement models for clustering mechanism. | (i) Future research directions may consider the work towards enhancing the rate of dynamic data transmission by automatically adjusting the network parameters and measuring the performance with the help of more simulations. |
| | Sah and Amgoth [141] | Network lifetime, alive nodes, and total commutative packets arrived at base station | (i) A new clustering framework has been presented for solar EH-WSNs.<br>(ii) The proposed framework utilized the hierarchical clustering approach. | (i) Future research directions may consider the work towards using advanced efficient harvesting devices for EH-WSNs. |
| | Kumar and Chaparala [142] | Energy consumption, throughput, delay, delivery ratio, drop ratio, and network lifetime | (i) A new clustering framework has been presented utilizing a hybrid optimization approach consisting of two optimization algorithms such as bacterial foraging and fruit fly optimization algorithm for cluster head selection in the EH-WSNs. | (i) Future research directions may consider the work towards using other advanced hybrid models of optimization algorithms for selecting the cluster heads. |

Table 7: Continued.

| Year | Author and reference details | Metric used for evaluating performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | Rathore et al. [143] | Energy consumption, delay, delivery ratio, and throughput | (i) A new clustering framework is presented utilizing a hybrid optimization approach consisting of whale and grey wolf optimizer.<br>(ii) In the proposed framework, the exploitation and exploration abilities are significantly improved with the help of the hybrid approach. | (i) Future research directions may consider the work towards using other advanced hybrid models of optimization algorithms for the clustering mechanism. |

presented. The framework focused on battery cost/budget along with maximizing the residual energy of the forwarding set. Both the abovementioned literature used the heuristic strategy. The heuristic approach is usually utilized for finding the solution to multiobjective optimization problems, and this fact is attested by currently available various kinds of literature. Further, for finding the solution in a relatively practical time, a heuristic algorithm can be used which utilized the concept of the trial-and-error approach. The heuristic method majorly provides reasonably accurate solutions.

Furthermore, the next important issue related to WSNs is regarding efficiently localizing the sensor nodes. An efficient optimization framework with multiobjective consideration is proposed in [169] for localizing the sensor nodes accurately to assess the geographical relevance of data. Next, coverage efficiency is also considered as one of the crucial issues for the performance evaluation of WSNs. Again, various literature have already been published with multiobjective formulations. They focus on enhancing the coverage with consideration of other desirable objectives also. The best solution is selected among multiple optimal solutions in the multiobjective optimization framework with consideration of a particular objective that is to be achieved [170]. Both the abovementioned literature used the evolution-based strategy. A population-based approach is used in an evolutionary multiobjective optimization framework. Here, in a particular iteration, multiple solutions take part, and a further new set of solutions evolves in the subsequent iteration. Next, derivative information is not needed in the evolution-based optimization framework, and therefore, their implementation is easy. Evolution-based optimization frameworks have a wide area of applicability and also the capability for providing solutions to complex optimization problems with multiobjective nature.

Moreover, the deployment strategies in WSNs have an immense impact on the performance since the strategies adopted in deployment have a direct relationship with the power efficiency of sensor nodes and therefore deployment issue is also considered an important constraint for WSNs. Therefore, it can be concluded that optimal deployment strategies improve the energy efficiency of WSNs and consequently lifetime of the network enhanced; also, these strategies contribute towards enhancing the overall performance of the network. In [171], metaheuristic algorithms based on various approaches are presented for resolving the deployment issue in WSNs. The metaheuristic approach is considered better than the heuristics approach. The metaheuristic framework [172] has two primary components such as randomization and the selection of the optimal solution. The randomization components contribute to avoiding the trapping of solutions at local optima. The best solution selection step helps in ensuring that the solutions will converge to optimality.

Next, in WSNs, two conflicting objectives such as efficient connectivity and network lifetime are required to be optimized by optimization formulation with multiobjective consideration for enhancing the overall performance [173]. The ultimate aim of the framework is to provide superior connectivity to the other schemes by considering the same energy conservation profile. Since superior connectivity along with enhanced lifetime are two prominent factors that greatly affected the performance, there is an urgent requirement of optimizing all objectives simultaneously by a single solution, but traditional multiobjective formulations are not capable to satisfy this requirement. The properly designed multiobjective optimization formulation can provide plenty of alternative solutions. Further, the location of these alternative solutions is nearby or on the Pareto optimal front. Also, only in a single run, plenty of Pareto optimal solutions can be discovered by nondominated sorting algorithm II.

Besides, in WSNs, energy-efficient or energy-aware routing frameworks are needed for the effective transmission of data packets. Various network attributes such as lifetime, overhead in communication, and availability of data are influenced by energy-efficient routing frameworks. Energy-efficient or energy-aware routing frameworks are aimed at maximizing system performance. For optimization and computational intelligence, bio-inspired algorithms are extensively used currently. Bio-inspired schemes consist of dual approaches such as reactive and proactive approaches. Bio-inspired schemes are capable enough for accomplishing adaptive routing, enhanced load balancing, and also discovering network topology [174].

Also, in WSNs, the bit error rate should be minimum, and on the other hand, signal-to-noise ratio should be maximum, and for achieving these conditions, transmission power should be increased. The increment in the transmission power has a severe impact on several key attributes of

Table 8: A detailed review of various energy balancing schemes.

| Year | Author and reference details | Metric used for evaluating the performance | Bullet points | Future research directions |
|---|---|---|---|---|
| 2012 | Yao et al. [151] | Transmission quality | (i) An efficient framework has been proposed for controlling the rates of source coding adaptively by appropriately selecting the most eligible data packets for transmission.<br>(ii) The proposed framework considers four primary factors for the selection of eligible packets such as power efficiency, energy cost, energy-neutral constraint, and also multimedia distortion reduction. | (i) The future research directions may consider extension towards utilizing other energy harvesting model since the current work utilizes the solar energy harvesting system. |
| 2013 | Gregori and Payaró [152] | Mean minimum completion time, percentage of solutions | (i) An optimal data transmission scheme has been proposed.<br>(ii) The proposed scheme considers the three constraints such as constraints for quality of service, data causality constraints, and also constraints for energy efficiency. | (i) The future research directions may consider extension towards fulfilling some other constraints for the optimal data transmission scheme. |
| | Roseveare and Natarajan [153] | Sum rate, inverse mean squared error | (i) Models have been presented for different applications in the EH-WSNs with system-wide utility.<br>(ii) The proposed models consider the presence of factors like uncertain resource availability with system parameters. | (i) The future research directions may consider extension towards developing the framework for utility maximization decentralized problems also the proposed framework will allow the problem decomposition. |
| 2014 | Wang et al. [154] | Average reward rate | (i) An optimal offline framework has been proposed for maximizing the weighted throughput.<br>(ii) Two optimal deterministic online algorithms have also been proposed along with the randomized algorithm. | (i) The future research directions may consider extension towards developing the framework for semionline algorithms. |
| | Berbakov et al. [155] | Throughput | (i) An efficient semianalytical framework has been presented.<br>(ii) The aim of the proposed framework is to evaluate the joint optimal transmission policy for EH-WSNs.<br>(iii) In the proposed framework, throughput has improved for a given deadline. | (i) The future research directions may consider extension towards considering other metrics for the evaluation of the proposed framework under different energy harvesting models. |
| 2015 | Michelusi and Zorzi [156] | Network utility | (i) Efficient access schemes are proposed with decentralized nature.<br>(ii) Also, each sensor node can individually decide whether to transmit a specific eligible packet or discarding the particular packet.<br>(iii) The decision on packets is based on certain factors such as estimation of packet's utility, the current state of energy harvesting mechanism, and finally energy profile.<br>(iv) The aim is to enhance the aggregate long-term utility of the packets. | (i) The future research directions may consider extension towards considering some other operational regimes since the current work identified two operational regimes such as the network-limited scenarios and energy-limited scenarios. |
| | Peng and Low [157] | Distinct packet delivery ratio | (i) A new framework has been proposed which is driven by query and having characteristics of energy-neutral with directed diffusion.<br>(ii) The proposed framework is aimed at maintaining the energy-neutral state at the network level.<br>(iii) The proposed framework results in enhanced data delivery and also the improved lifetime of the network. | (i) The future research directions may consider extension towards considering some more performance metrics for evaluating the performance of the proposed framework. |

Table 8: Continued.

| Year | Author and reference details | Metric used for evaluating the performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | Zordan et al. [158] | Average reward, percentage of used slots, average fidelity | (i) Efficient policies have been proposed to control lossy data compression over fading channels. (ii) The proposed schemes consider the replenishable energy buffer along with the specific process having stochastic energy input. | (i) The future research directions may consider extension towards modeling of the coupled dynamics of multiple energy harvesting sensors with multiuser scenarios. |
| 2016 | Zhou et al. [159] | Average mean square error | (i) A new framework has been proposed for investigating the source estimation problem in EH-WSNs. | (i) The future research directions may consider extension towards finding the more efficient solution to the stochastic constraints since the current proposed framework may increase the estimation distortion. |
| | Gong et al. [160] | Throughput | (i) An efficient centralized scheme has been proposed for achieving the optimal throughput by utilizing the monotonicity which exists in the problem structure. (ii) Further, a distributed suboptimal scheme has been proposed in a game-theoretic approach. (iii) Next, the source and the relays are responsible for the proposed framework to iteratively update two primary factors such as beamforming vector and energy harvesting schedule. | (i) The future research directions may consider extension towards developing relay network with multihop transmission and also having energy harvesting constraints. |
| | Sunny [161] | Quality of monitoring | (i) An efficient joint scheduling and sensing allocation problem has been formulated which is attributed with a long-term time-averaged characteristic. (ii) The formulated problem considers the finite data buffers, specific energy profile, and constraints such as quality of service related to battery and certain data constraints. | (i) The future research directions may consider extension towards utilizing the variable energy profile with different size data buffers also considering various other constraints. |
| 2017 | Tang et al. [162] | Throughput | (i) The energy harvesting and information processing framework has been proposed which is based on time switching as well as power splitting relaying. | (i) The future research directions may consider extension towards efficient optimization of two crucial factors such as time switching and power splitting relaying and again evaluating the proposed framework in the new environment. |
| 2018 | Aoudia et al. [163] | Dead ratio, average packet rate, and energy efficiency | (i) A novel framework has been proposed for optimal energy management. (ii) The proposed framework considers reinforcement learning. (iii) The proposed framework efficiently manages the energy management adaptively with respect to the time-varying environment. | (i) The future research directions may consider extension towards considering some other efficient technique since the current work considers reinforcement learning. |
| 2019 | Mabon et al. [164] | State of charge | (i) An efficient node architecture has been proposed with the capabilities of high-range communication with energy-autonomous characteristics. (ii) Also, an optimization framework has been proposed for the energy harvesting and node's storage elements. | (i) The future research directions may consider extension towards considering some other energy harvesting environment since the current work considers solar energy harvesting. |
| 2020 | Clemente et al. [165] | Power conversion efficiency | (i) An investigation is conducted for analyzing the energy balance of a node. (ii) The investigation considers the three | (i) The future research directions may consider extension towards considering some other energy harvesting environment since the |

Table 8: Continued.

| Year | Author and reference details | Metric used for evaluating the performance | Bullet points | Future research directions |
|---|---|---|---|---|
| | | | specific energy harvesting technologies such as piezoelectric, photovoltaic, and radiofrequency/Wi-Fi. | current work considers the three specific energy harvesting technologies such as piezoelectric, photovoltaic, and radiofrequency/Wi-Fi. |

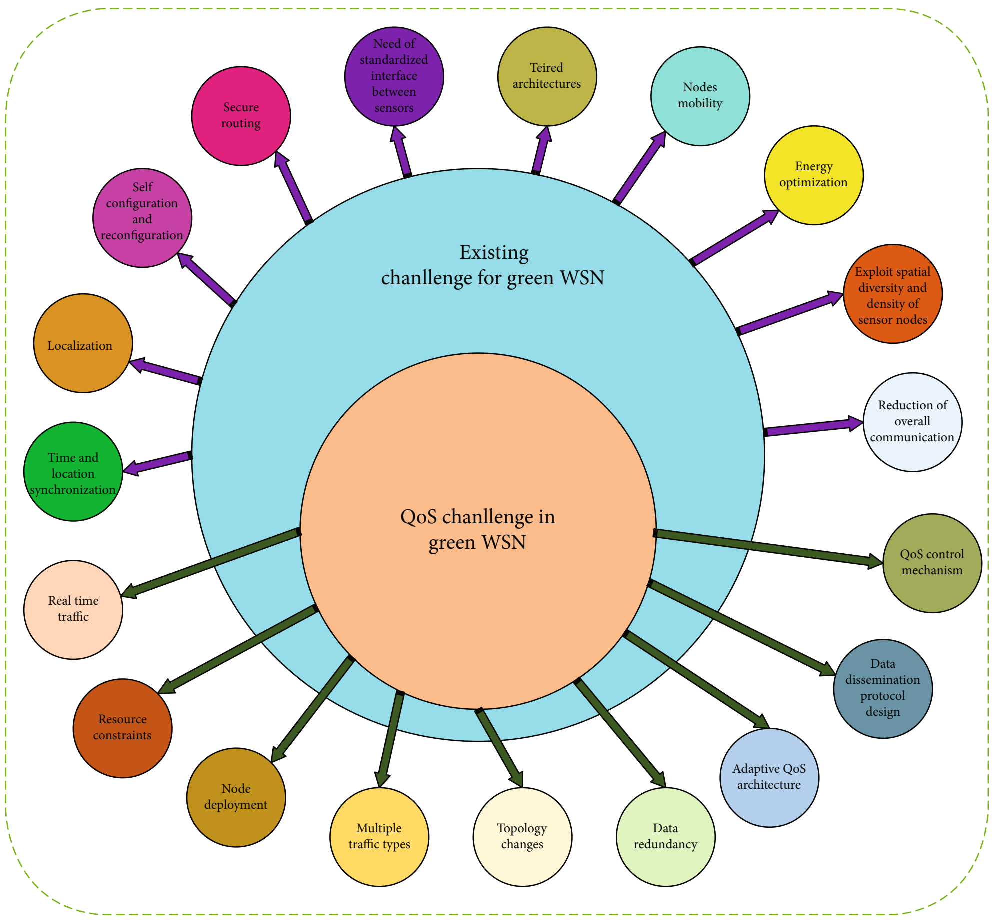


Figure 11: A broad classification of various existing challenges for green WSNs.

the network, namely, minimization of interference, energy efficiency, and lifetime. Hence, trade-offs among conflicting objectives can be attained by utilizing efficient multiobjective optimization frameworks. In [175], for minimizing the interferences and maximizing the throughputs, a multiobjective memetic algorithm is used to design efficient power allocation techniques along with a spectrum sensing module. Memetic algorithms are having the computational intelligence structures; further, the trial-and-error approach is used for discovering the Pareto optimal solution set.

Next, in WSNs, reliability and delay are also important parameters that need to be optimized for enhancing the system performance. In [176], an efficient routing framework is presented which utilized the multiobjective optimization approach. One of the most desired objectives is the implementation of quality of service, and this objective conflicts with other objectives such as lifetime, delay, and network cost. The routing optimization model utilized the fuzzy random variables for representing the randomness and fuzziness of the objectives and constraints. The mathematical notations are used for representing human reasoning in the Fuzzy logic approach. Fuzzy logic utilized the inference rules and linguistic variables for establishing the approximation for the truth value of a proposition.

It should be noted that high transmission power is required for increasing the transmission range of sensor nodes and consequently the degree of sensor node increases, but it has a high impact on energy efficiency and results in reduced performance in terms of energy-saving. Also, one of the attributes of WSN known as network reachability is

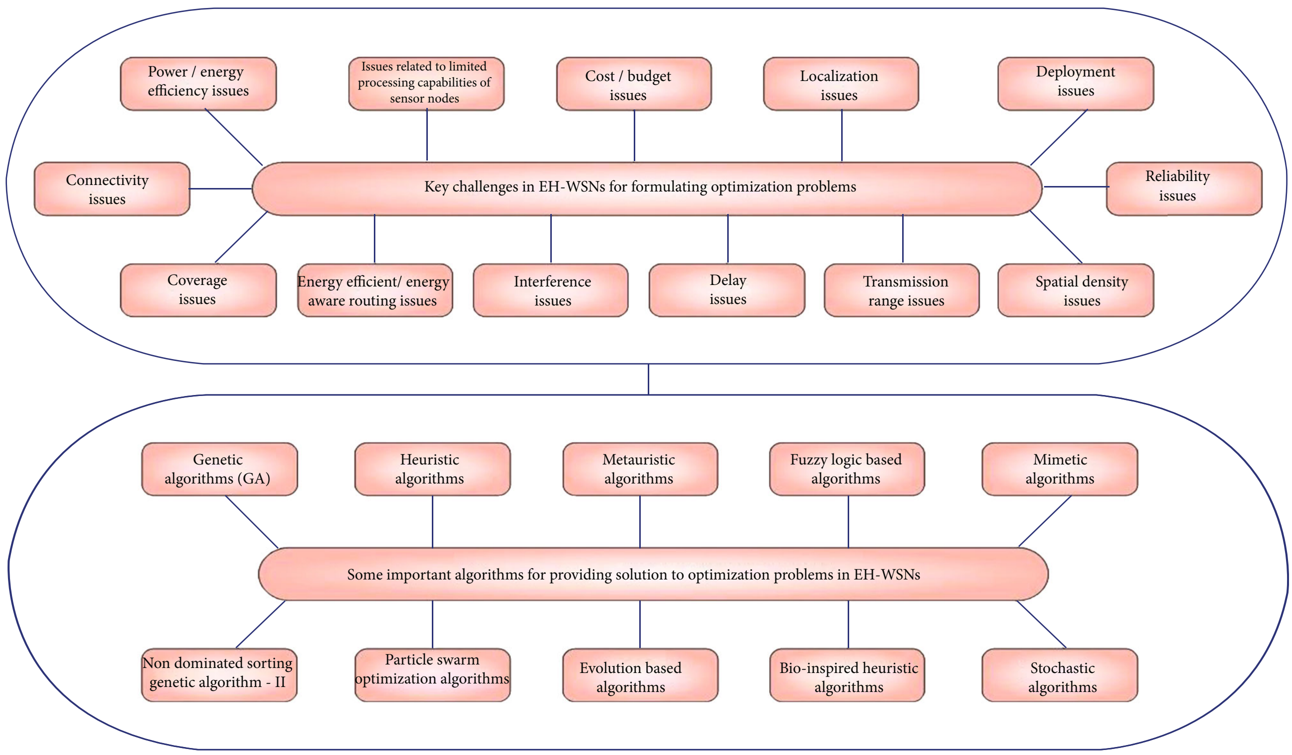


Figure 12: Optimization challenges and solutions in EH-WSNs.

usually low in case of poor connectivity of WSNs; on the other hand, strong connectivity in the network requires a high demand of power and consequently decreases the quality of service in WSNs. An extensive investigation is needed to analyze the optimal transmission power requirement of a sensor node. Further, for obtaining the energy-efficient clustering-based routing framework, an optimization formulation with multiobjective consideration is presented in [177]. The trade-offs among total packets delivered to the base station, the lifetime of the network, energy utilization, and dead nodes are achieved in the proposed framework. Particle swarm optimization is used in the framework. Particle swarm optimization is based on swarm behavior. In recent years, various optimization formulations have been solved by the particle swarm optimization algorithm, and therefore, it has attained immense recognition as compared to other optimization algorithms.

Also, in WSNs, plenty of tiny sensor nodes are deployed densely; also, the spatial distribution of sensor nodes affected the overall performance which results generally in terms of the error in the reconstruction of the physical signal. In a distributed tracking framework, the sensors' assignment to fusion centers in a dynamic fashion is presented in [178]. A framework is proposed in which the original problem is decomposed into subproblems by taking the concept of a genetic algorithm approach for finding real-time suboptimal solutions. Over the last two decades, genetic algorithm has been proved as an efficient search technique for solving various optimization problems. The genetic algorithm is inspired by Darwin's principle of natural evolution and starts with a set of randomly generated candidate solutions, denoted as population. Each individual in the population corresponds to a candidate solution to the problem, and it is represented by a genetic code.

## 6. Trendwise Technical Analysis of Energy Harvesting Technologies Development with Future Aspects

The development trends for various energy harvesting techniques can be majorly divided into four eras yearwise as illustrated in Figure 13. Development trends in the summarized form with the scientific progress for different energy harvesting technologies have been demonstrated in this figure.

The first era covers the development activities in a duration of ten years, i.e., from 2000-2010. The key attributes of this era in terms of significant development for energy harvesting technologies are the development of energy harvesting devices with enhanced fabrication technologies and further inclination of trends towards developing the hybrid model for energy harvesting systems.

The second era covers the development activities in the duration of five years, i.e., from 2010-2015. The significant key advancement towards energy harvesting technique can be highlighted as development towards triboelectric nanogenerators technology, development of multiple system architectures for energy harvesting devices and also the development of hybrid energy harvesting system model, and further inclination of trends towards integrating the Industry 4.0 with energy harvesting technologies.

The third era covers the development activities in the duration of five years, i.e., from 2015-2020. The important key attention-seeking developments for energy harvesting

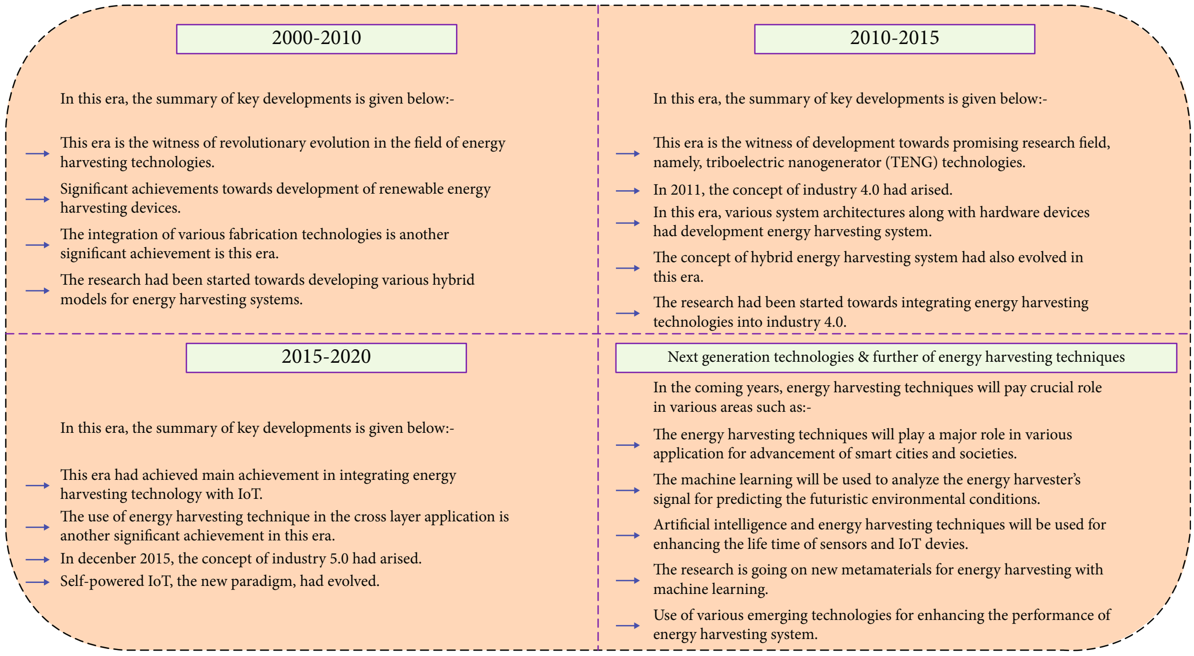


Figure 13: Trendwise technical analysis of energy harvesting technique development with future aspects.

technique can be listed as the integration of energy harvesting technology with IoT; next, significant development is the use of energy harvesting technique with the cross-layer application, with the evolution of Industry 5.0 in December 2015 and further inclination of trends towards developing self-powered IoT.

Furthermore, the trends have started towards exploring the use of energy harvesting technologies for uplifting the current scenario of smart cities and societies as well and in the future; this trend will be further boosted with the acceleration towards the development of the technologies for small-scale self-powered devices with the system-level implementation. Next, machine learning will be used for analyzing the signal of the energy harvester for predicting the futuristic environmental conditions. The research is going on exploring new metamaterials for energy harvesting with machine learning. Further, research is going on exploring new emerging technologies for enhancing the performance of the energy harvesting system.

## 7. Conclusion

In this systematic survey, we have conducted a deep study for the energy optimization issue of EH-WSNs. The ultimate aim is to enhance the life span of sensor nodes. In this high-level systematic and taxonomical survey, we have organized the energy optimization strategies for EH-WSNs into eleven main classes such as schemes based on optimization of radio, schemes based on optimization of the energy harvesting process, schemes based on reduction of data in the system, schemes based on sleep/wake-up policies, schemes based on load balancing, schemes based on optimization of power needed by the hardware devices in the system, optimization of communication mechanisms, schemes based on optimization of battery operations, mobility-based schemes, and finally energy balancing schemes. This systematic and taxonomy survey also provides a progressive detailed overview and classification of various optimization challenges for the EH-WSNs that require attention from the researcher followed by a survey of corresponding solutions for corresponding optimization issues. Further, this systematic and taxonomical survey also provides a deep analysis of various emerging energy harvesting technologies in the last twenty years of the era. From the study, it can be concluded that energy harvesting technology can be used as an alternative source of energy for sensor nodes, but environmental heterogeneity compels us to think about strategies for effective utilization of harvested energy and energy optimization strategies play a major role in achieving this objective. There is a scope of enhancing the efficiency of the energy harvesting system, and therefore, a lot of research is still going on optimizing the energy harvesting mechanism. Although optimization of the energy harvesting mechanism possesses several challenging issues that need to be handled effectively, further, it should be worth mentioning that we should explore the possibility of new sources of energy for energizing the tiny sensor nodes. Besides, a hybrid approach can be considered for handling the energy scarcity issue of tiny sensor nodes that comprising all three pillars of energy in WSN, namely, harvested energy from the environment, batteries, and finally wireless energy transfer mechanism, but again this approach is an open research area and sincere efforts are needed to counter several challenges and, in this way, a sustained WSN may be realized.

## Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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*Research Article*

# Task Migration Based on Reinforcement Learning in Vehicular Edge Computing

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Multiaccess edge computing (MEC) has emerged as a promising technology for time-sensitive and computation-intensive tasks. With the high mobility of users, especially in a vehicular environment, computational task migration between vehicular edge computing servers (VECSs) has become one of the most critical challenges in guaranteeing quality of service (QoS) requirements. If the vehicle's tasks unequally migrate to specific VECSs, the performance can degrade in terms of latency and quality of service. Therefore, in this study, we define a computational task migration problem for balancing the loads of VECSs and minimizing migration costs. To solve this problem, we adopt a reinforcement learning algorithm in a cooperative VECS group environment that can collaborate with VECSs in the group. The objective of this study is to optimize load balancing and migration cost while satisfying the delay constraints of the computation task of vehicles. Simulations are performed to evaluate the performance of the proposed algorithm. The results show that compared to other algorithms, the proposed algorithm achieves approximately 20–40% better load balancing and approximately 13–28% higher task completion rate within the delay constraints.

## 1. Introduction

With the rapid development of Internet of Things technologies, numerous complex applications such as automatic driving, augmented/virtual reality, and image recognition have emerged recently. These applications are usually time-sensitive and computation-intensive; they require a large amount of computation resources and high quality of service (QoS) [1]. These high-complexity services are difficult to guarantee; therefore, users offload their computation-intensive tasks to a remote cloud server with sufficient computational resources. However, processing the exponentially increasing requests in the cloud and long-distance communication between users and remote cloud servers leads to considerable latency, which results in failure to meet the QoS requirements. To overcome this problem, multiaccess edge computing (MEC) has emerged as a promising technology [2]. Compared to centralized cloud servers, MEC servers with computing and storage resources are deployed at the edge of networks. Offloading computation-intensive tasks to MEC servers that are geographically closer to users can better fulfil the QoS requirements and improve reliability of computation tasks.

One of the challenges of an MEC system is mobility; this is because users move across the coverages areas of MEC servers [3]. When a user moves out of the coverage area of the current serving MEC server, the system needs to perform task migration from the current MEC server to the target MEC server. Task migration in a vehicular environment with high mobility should be carefully considered. Because the number of task migrations in high-mobility environments is greater than that in low-mobility environments, the choice of the target MEC server highly influences the performance of an MEC system.

Load balancing among vehicular edge computing servers (VECSs) is necessary to meet the QoS requirements of computational tasks and also improve the throughput of the system. A VECS acts as the MEC server in a vehicular environment. Task migration considering load balancing is beneficial because it can reduce the computational congestion of VECSs, which shortens the computation time required to process a task and improve task throughput in a VECS system. However, task migration requires additional costs of migration time and computation resources. Accordingly, we propose an efficient computational task migration strategy to improve the balance of loads in VECSs and minimize the migration cost in a vehicular environment. We adopt a cooperative VECS group environment that can collaborate with the VECSs in the group [4]. Migrating the tasks to the nearest VECS can result in unequal distribution of loads at a certain VECS; thus, the task may not be completed within the delay constraint due to overload. In addition, the throughput of a VEC system may reduce. Thus, we adopt a task migration strategy in the cooperative VECS group environment to increase the number of candidate VECSs for migration. We can select the best VECS among the candidate VECSs and balance the loads of the VECSs. Load balancing can improve not only the fulfilment of the QoS requirements of a task but also the throughput of computational tasks in a VEC system.

The remainder of this paper is organized as follows. Section 2 introduces related works on computational task migration and load balancing. Section 3 describes the system model and proposed algorithm using reinforcement learning (RL). Section 4 presents and discusses the results of the simulation. Finally, Section 5 concludes the study.

## 2. Related Work

In this section, we discuss two main categories of related work: computational task migration and load balancing. The high mobility of vehicles across multiple VECSs as well as an increase in the number of vehicles can lead to unbalanced loads among VECSs, which can reduce the QoS and lead to computation delay. Therefore, some studies on load balancing with offloading optimize server selection [5–7].

In [5], authors proposed a joint load balancing and offloading method to maximize the system utility in VEC networks. They designed an algorithm to adopt task computation delay to formulate the system utility. By jointly optimizing server selection, offloading ratio, and computation resources among VECSs, the requirements could be satisfied using a logarithmic utility function. The authors in [6] proposed a task offloading method based on a heuristic algorithm to achieve load balancing of the computation resources among VECSs. The proposed method was aimed at minimizing the processing delay by utilizing the computation resources of the VECS more efficiently. In [7], the load-balancing problem was handled in a distributed *software-defined networking* framework using an M/M/1 queuing system that optimized the migration operations that select the sever to which the task should be migrated. To achieve better load balancing, the trade-off between load balancing and migration operation costs was optimized. The load consisted of each server's response time; the migration cost was the sum of the initial and target servers' response time. The loads were balanced by lowering the average response time. In this study, we perform load balancing with the number of computational task requests and reduce migration cost with the size of the task; therefore, loads are balanced by lowering the difference between the number of tasks at each VECSs. In addition, we adopt RL. Because of the high mobility and time-sensitive services, the environment becomes more complex and dynamic; thus, there are limitations in obtaining optimal solutions with heuristic algorithms.

Task migration has been seen as an efficient solution to deal with the QoS and latency issues faced due to the high mobility of users and high-complexity applications. There are few studies, addressing the task migration problem, that utilize RL, such as Sarsa [8], Q-learning [9, 10], and deep Q-network (DQN) [10–13].

The authors in [8] proposed an on-policy RL- (i.e., "Sarsa-") based computation migration method to determine the optimal VECS. The aim was to minimize the overall response time of the offloaded computation tasks. The decision was based on the VECS hosting the previous task, task characteristics, and vehicle locations. In [9], the authors addressed joint task offloading and migration schemes based on Q-learning to obtain the maximum system revenue. The decision was made based on the property of computation tasks, mobility of users, and cell sojourn time of users.

In [10], the authors considered a single user scenario by exploiting the predefined mobility of the user; the user passes through many VECSs and the corresponding services decide the migration strategy and communication strategy. The authors proposed a Q-learning and DQN-based service migration algorithm to minimize the migration and communication costs, respectively, for detailed evaluation. In [11], a service migration algorithm based on DQN was proposed, which considered the dynamics of the network bandwidth, battery level of mobile devices, and remaining computation. The proposed algorithm was aimed at minimizing the total cost, which consisted of delay and energy consumption. The authors in [12] proposed DQN-based computation migration and resource allocation; the goal was to minimize the total cost, which consisted of the delay cost, energy computation cost, and bandwidth cost. In [13], a DQN-based algorithm was designed for task migration and resource management at the network edge. With the model mobility, the goal was to make the right decision to balance the migration cost and data transfer cost to reduce the overall cost.

As discussed above, some studies were aimed at maximizing the system utility or minimizing the overall delay of tasks. In contrast, in this study, we aim to balance the loads of the VECSs and minimize the migration cost while satisfying the vehicle requirements. In addition, we adopt RL to better manage the dynamic and complex environments in VEC.

## 3. Methodology

*3.1. System Model.* As shown in Figure 1, we consider a VEC system consisting of $M$ VECSs, each of which is deployed at a roadside unit (RSU). The VECSs communicate among each other through backhaul links, which allows load balancing among them. The RSUs are connected to a base station equipped with a VECS controller. The VECS controller can collect information on vehicles and VECSs in a system for making migration decisions for load balancing of VECSs to meet the task requirements of the vehicles.

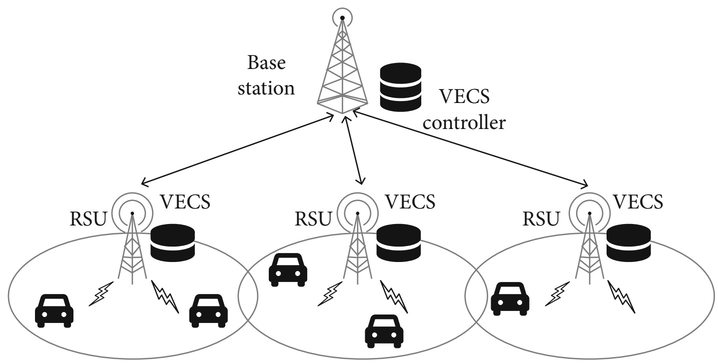


Figure 1: Vehicular edge computing system (VECS) model.

In a system, $N$ vehicles are deployed following a Poisson distribution on the road. The vehicles run at speed $v$. Vehicle $n$ has a computation-intensive task, which can be described as $s_n = \{\lambda_n, \eta_n, T_n^{\max}\}$, where $\lambda_n$ denotes the size of the computation task, $\eta_n$ denotes the computation resources required to process the task, and $T_n^{\max}$ denotes the delay constraint of the task.

Considering vehicle mobility, we focus on a dynamic scenario in which vehicles move across multiple VECSs. Once a vehicle moves out of the coverage of its serving VECS, the VECS controller should decide whether to migrate the computation task of the vehicle to another VECS. The VECS controller makes migration decisions to satisfy the QoS constraints of the task and improves the throughput of the system. The following models were used to describe the system:

*3.1.1. Communication Model.* The communication model depicts the communication time for a computational task to be transmitted from vehicle $n$ to VECS $m$ via a wireless channel. Each vehicle $n \in N$ offloads its computation-intensive task to one of the VECSs in its communication coverage. The data transmission rate between vehicle $n$ and VECS $m$ is given as

$$R_{n,m} = B_n \log_2\left(1 + \frac{P_n H_{n,m}}{\sigma^2}\right), \tag{1}$$

where $B_n$ and $H_{n,m}$ denote the channel bandwidth and channel gain between vehicle $n$ and VECS $m$, respectively; $P_n$ is the transmission power of the vehicle; and $\sigma^2$ is the power level of the white noise.

The communication time for offloading the computation task of vehicle $n$ to VECS $m$, $T_n^{\text{trans}}$, is given as follows:

$$T_n^{\text{trans}} = \frac{\lambda_n}{R_{n,m}}. \tag{2}$$

The size of the computation result is smaller than that of the offloading task; therefore, the download time from the VECS to the vehicle is not considered.

*3.1.2. Computation Model.* The computation model describes the computation time required to execute a computational task. The computing capacity of the VECS $m$ is denoted by $C_m$, which is measured by the CPU cycles per second. It is assumed that the computation requests that are hosted on VECS $m$ share computing capacity $C_m$ evenly. The computing delay is expressed as follows:

$$T_n^{\text{comp}} = \frac{\psi \cdot \eta_n}{C_m / \Sigma_{n\in N} \phi_n^m}, \tag{3}$$

where$\psi$denotes how many remaining CPU cycles are required. Further, $\phi_n^m$ denotes whether task $s_n$ is hosted on VECS $m$. In the equation, the computation time of VECS increases linearly with the number of computational requests in the VECS, which can lead to unreliable services and increase in the latency of computational tasks. By balancing the computation loads among VECSs, the QoS requirements and throughput of the system can be improved as congestion and bottlenecks of the VECS are reduced.

*3.1.3. Migration Model.* The migration time is the time required to transmit a task from VECS $m$ to VECS $m'$ via backhaul links when a VECS controller decides to migrate computation task $s_n$. The migration time is expressed as follows:

$$T_n^{\text{mig}} = \begin{cases} 0, & \text{if } m = m', \\ \dfrac{\lambda_n}{R_b}, & \text{if } m \neq m', \end{cases} \tag{4}$$

where $R_b$ is the bandwidth between VECSs via backhaul links.

Computational migration caused by the mobility of vehicles incurs additional costs, such as the cost for computational replication from VECS $m$ to VECS $m'$ and the resource release of current hosting VECS $m$ [14]. The migration cost is determined by the size of task $n$ to be migrated from VECS $m$ to VECS $m'$; the migration cost is denoted as follows, where $\mu$ is a positive coefficient:

$$C_n^{\text{mig}} = \begin{cases} 0, & \text{if } m = m', \\ \mu|\lambda_n|, & \text{if } m \neq m'. \end{cases} \tag{5}$$

*3.1.4. Load Balance Model.* One of the goals of this study is to balance the loads among VECSs. The computing load of VECS $m$ can be calculated as follows:

$$L_m = \sum_{m\in M}\sum_{n\in N} \varnothing_n^m, \tag{6}$$

where $\varnothing_n^m$ is a binary variable that determines whether task $s_n$ is hosted on VECS $\text{vecs}_m$, which is denoted by

$$\varnothing_n^m = \begin{cases} 1, & \text{if } s_n \text{ is hosted on } \text{vecs}_m, \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

The average computing load of all VECSs is calculated as

$$L = \frac{1}{M}\sum_{m=1}^{M} L_m. \tag{8}$$

To determine whether the computing load is distributed fairly among the VECSs in the system, load balance is measured by the deviation of the computing load at each VECS [15]. In this study, we define the load-balancing factor LB as follows:

$$\text{LB} = \frac{1}{M}\sum_{m=1}^{M} |L_m - L|. \tag{9}$$

*3.1.5. Problem Definition.* Considering the mobility of vehicles, a VECS controller decides whether and where to migrate the computational task among VECSs. In this study, we aim to achieve the goal of balancing the loads of VECSs and minimizing the migration cost while satisfying the delay constraints of the computation tasks. The two objectives are defined as a weighted sum with weight factor $\omega \in [0, 1]$. Consequently, the problem is formulated as

$$\begin{aligned} \min \quad & \omega \cdot \text{LB} + (1-\omega)\cdot C^{\text{mig}}, \\ \text{s.t.} \quad & T_n^{\text{total}} < T_n^{\max}. \end{aligned} \tag{10}$$

$C^{\text{mig}}$ denotes the total migration costs of the tasks to be migrated into a system. The total computation time for vehicle $n$ is given as

$$T_n^{\text{total}} = T_n^{\text{trans}} + \sum_{i=0}^{\tau} T_n^{\text{mig}} + T_n^{\text{comp}}, \tag{11}$$

where $\tau$ is the number of migrations that occur during the task computation time. The size of the problem can increase rapidly as the number of vehicles and VECSs increase. Instead of using the existing optimization strategy, in this study, we propose an RL-based strategy to address this problem.

*3.2. Proposed Algorithm.* In this section, we propose a computation migration strategy based on RL. The VECS controller acts as an agent. The controller can observe the load states for all VECSs and vehicle information and make a migration decision to balance the loads and minimize the migration cost while satisfying the delay constraint of the computation task.

The Q-learning algorithm is a model-free RL algorithm that learns to determine the optimal policy that maximizes the expected reward. Q-learning consists of a set of states $S$, set of actions $A$, and set of rewards $R$. The agent chooses an action according to the optimal policy based on its current state. The state transitions from one state to another by taking action $a$. The Q-function is updated as follows:

$$Q(s, \text{a}) = Q(s, a) + \alpha\left[r + \gamma \cdot \max_a Q\left(s', a'\right) - Q(s, a)\right], \tag{12}$$

where $s$ and $a$ indicate the state and action at time $t$, respectively. When an agent selects action $a$ at time $t$, state $s$ enters a new state $s'$. Here, $\alpha$ represents the learning rate. $\gamma$ and $r$ represent the discount factor and reward at time $t+1$, respectively. The optimal Q-function can be expressed as

$$Q^*(s, a) = \max_a Q\left(s', a'\right). \tag{13}$$

However, the high dimensionality of the state and action spaces reduces the efficiency of the Q-learning algorithm. To address this problem, we propose a deep Q-learning-based migration strategy that predicts the reward of each action using the DQN, a trained neural network. Deep Q-learning is more applicable to high-dimensional environments with large and complex state spaces.

Deep Q-learning uses a neural network to learn $Q^*(s, a)$. The Q-function in the DQN is defined as $Q^*(s, a\,;\theta)$, where $\theta$ stands for the weights of the main DQNs. Then, the network is trained by minimizing the loss function, denoted as $\text{Loss}(\theta)$, which is given by

$$\text{Loss}(\theta) = \mathbb{E}[y - Q(s, a\,;\theta)]^2, \tag{14}$$

where $y = r + \gamma \cdot \max_{a'} Q(s', a'\,;\theta')$ is the target Q-value, and the weights $\theta'$ are updated to $\theta$ periodically. Algorithm-based deep Q-learning is shown in Algorithm 1. The controller observes state $s$ and takes action $a$ at every interval $t$. The elements in the RL model are defined as follows:

(1) *State*: to optimize the load balance and reduce the migration cost, the state reflects the task information of the vehicles, list of VECSs serving $N$ tasks, total loads of a VEC system, and migration decision variable. Therefore, state $s$ is defined as

$$s = \{V_1, V_2, \cdots, V_n, l\}, \tag{15}$$

where $V_n$ denotes $\{\lambda_n, e_n, d_n\}$. $\lambda_n$ represents the size of the computation task $n$, $e_n$ represents the VECS that hosts computation task $n$, and $d_n$ denotes a binary variable that indicates whether the task needs to be migrated. $l$ denotes the sum of the computing loads of the serving VECSs.

Initialize main DQN $Q(s, a; \theta)$ with random weights $\theta$
Initialize target DQN $Q(s, a; \theta')$ with weights $\theta' = \theta$
Initialize replay memory $D$ to capacity $N$
**For** each episode **do**
  Initialize initial state $s_0$, reward $r_0$
  **For** time slot $t = \tau,\ 2\tau \cdots \Gamma$ **do**
    The controller acquires information about vehicles, tasks, and VECS by interacting with the environment
    **If** the random number < $\epsilon$:
      Select action $a_t = \text{argmax}_a Q(s_t, a_t; \theta)$
    **Else**:
      Randomly select action $a_t$
    Execute action $a_t$ at controller, observe reward $r_t$ and next state $s_{t+1}$
    Store the tuple $<s_t, a_t, r_t, s_{t+1}>$ in $D$
    Randomly sample a minibatch of tuple $\{<s_j, a_j, r_j, s_{j+1}>\}_{j=1}^{J}$ from $D$
    **If** episode terminates at $j+1$, then
      $y_j = r_j$
    **Else**:
      $y_j = r_j + \gamma \bullet \max_{a'} Q(s_{j+1}, a'; \theta')$
    Perform a gradient descent step on $\text{Loss}(\theta)$ with respect to the network parameters $\theta$, where loss function is $\text{Loss}(\theta) = (1/J)\sum[y_j - Q(s_j, a_j; \theta)]^2$ and update $\theta' = \theta$
    Terminate when all the vehicles are out of simulation region
  **End for**
**End for**

Algorithm 1: Deep Q-learning method.

Table 1: Parameters used in simulation.

| Parameter | Value |
|---|---|
| $B$ | 10 MHz |
| $\lambda$ | [100,150] MB |
| $\eta$ | [0.4,0.5] Gcycles/MB |
| $P_n$ | 1 W |
| $C_m$ | 10 GHz |
| $\mu$ | 0.002/MB |
| $\sigma^2$ | $10^{-11}$ mW |

(2) *Action*: for each time step, the controller selects and executes an action based on its current state. In the proposed VECS network, the controller determines where to migrate tasks for optimizing load balancing and migration cost in a system. Accordingly, the action is denoted as follows:

$$a = \{a_1, a_2, \cdots, a_n\}, a_n \in M, \tag{16}$$

where $a_n$ refers to the serving VECS of task $n$. If $a_n = e_n$, the computation task does not migrate. If $a_n \neq e_n$, then the task is migrated to $a_n$.

(3) *Reward*: after each time step, the controller receives feedback from the environment, which is reward $r$. In general, the RL reward is related to optimization. The goal of our optimization problem is to minimize the average variation in the VECS loads and migration cost. Therefore, we formulate the function of negative reward as follows:

$$r = \omega \cdot \text{LB} + (1-\omega) \cdot C^{\text{mig}}. \tag{17}$$

## 4. Experimental Comparison

To illustrate the performance of the proposed algorithm, we considered seven VECSs connected to the RSU environment. The radius of the VECS was 250 m, and the capability of each VECS was 10 GHz. The mobility dataset of San Francisco city was used in the simulation [16]. The cooperative VECS group could have a maximum of 100 vehicles with computation-intensive tasks. Both the size of each task and the required number of CPU cycles per bit followed a random distribution with [100,150] MB and [0.4, 0.5] Gcycles/MB, respectively. The path loss between the RSU and a vehicle was modeled as $140.7 + 36.7 \log_{10}(\text{distance (km)})$ [17]. The deep Q-learning parameters were $\gamma = 0.9$ and $\epsilon = 0.9$. The capacity of the replay memory was 500, and the size of the minibatch was 32. The parameters used in the simulations are listed in Table 1.

In this study, weight factor $\omega$ and time interval $\tau$ are strategic parameters. Weight $\omega$ trades off between the load balance and the migration cost in the reward function (Equation (17)). Interval $\tau$ represents the frequency with which the controller makes migration decisions. Figures 2, 3, and 4

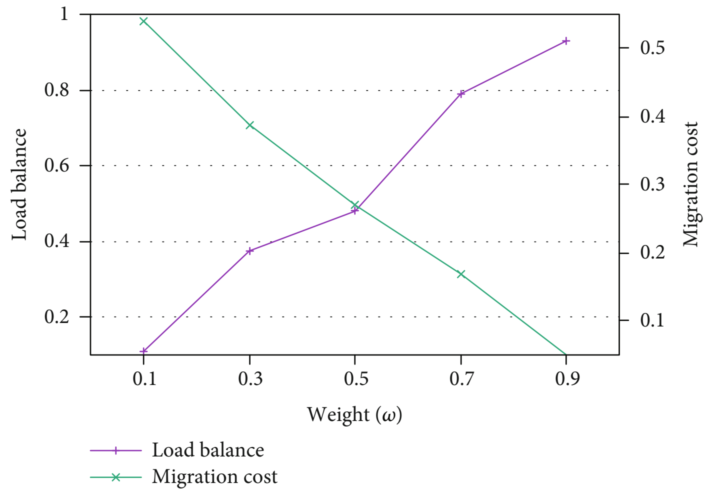


FIGURE 2: Effect of weight on load balancing and migration cost.

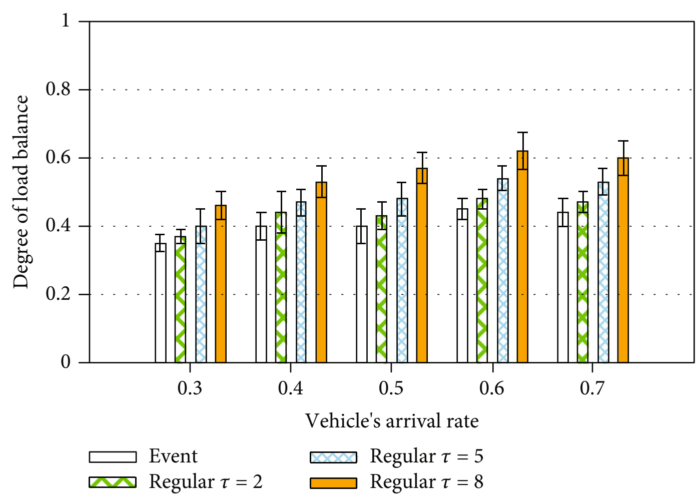


FIGURE 3: Degree of load balance for different intervals $\tau$.

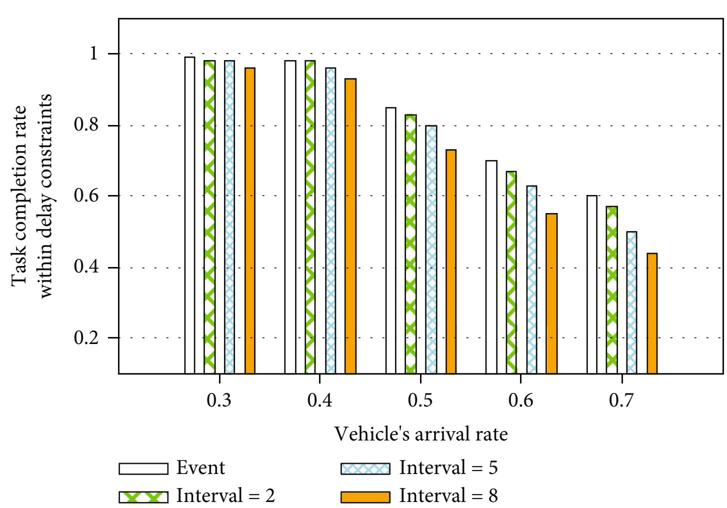


FIGURE 4: Task completion rate for different intervals $\tau$.

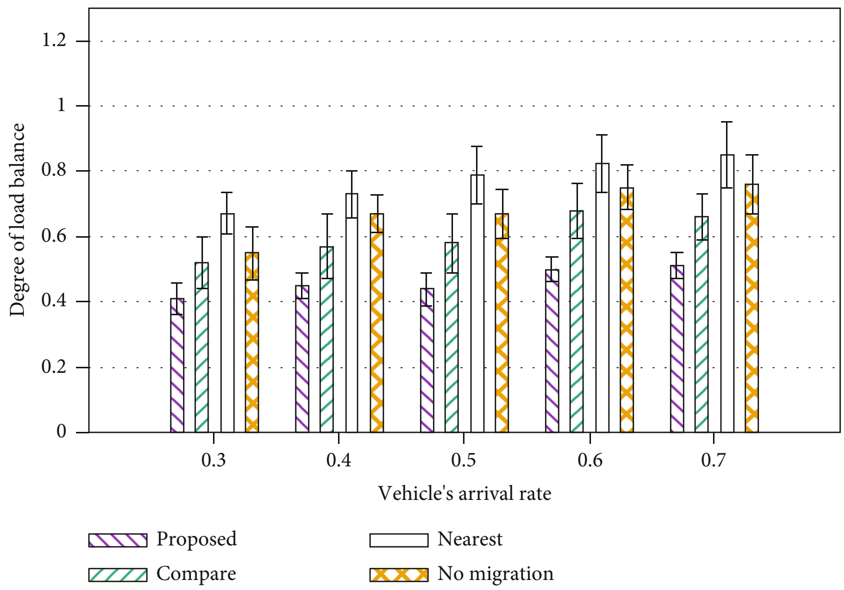


Figure 5: Comparison of the degree of load balance for different arrival rates.

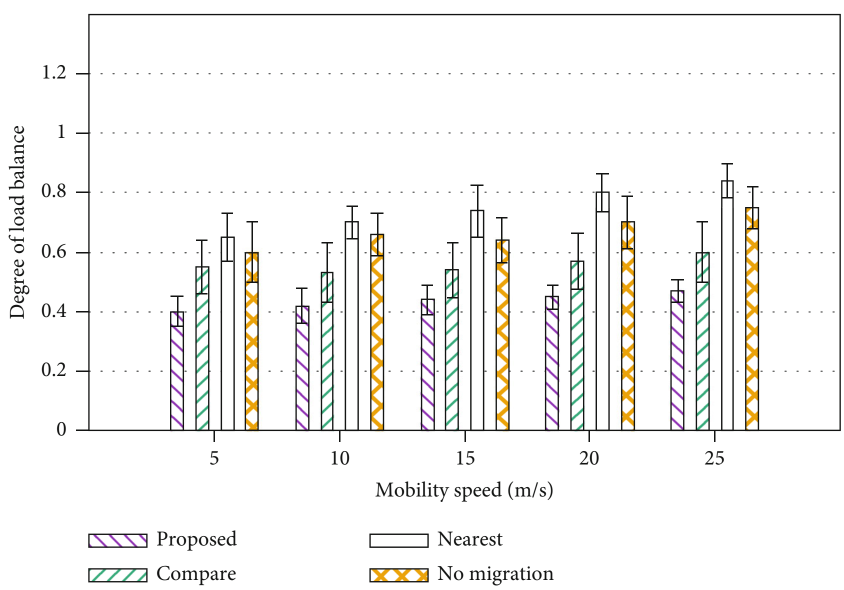


Figure 6: Comparison of the degree of load balance for different mobility speeds.

show the manner in which weights $\omega$ and intervals $\tau$ affect the system performance.

To find optimal weight $\omega$ for load balancing and migration cost, we evaluate the performance by varying weight $\omega$ when the arrival rate is 0.5 and the vehicle's mobility is 15 m/s (Figure 2). In the following simulations, we set weight $\omega$ to 0.5, which affected the load balancing and migration cost equally.

To analyze the effect of interval factor $\tau$ on the performance, we measured the degree of load balance and task completion rate within the delay constraints, as shown in Figures 3 and 4. In the figures, "Event" indicates that the controller makes migration decisions whenever a vehicle moves between adjacent VECSs. "Regular $\tau = 2$, 5, or 8" indicate that the controller regularly makes migration decisions every $\tau = 2$, 5, or 8. Compared to regular $\tau = 2$, 5, and 8, Event shows approximately 6%, 14%, and 26% better load balancing performances, respectively. Event has higher completion rates within the delay constraints of approximately 3%, 8%, and 16%, respectively. However, as the number of vehicles increases, Event puts too much pressure on the controller. Therefore, we set the VECS controller to make migration decisions at regular intervals of $\tau = 5$ considering the controller's burden, load balancing, and latency.

The performance of our proposed DQN-based migration algorithm is compared with three algorithms: *Compare* [7], *Nearest*, and *No Migration*. In the *Compare* and proposed algorithms, the optimization problem is formulated for reducing migration cost and load balancing. The *Compare* algorithm makes the migration decision with the response

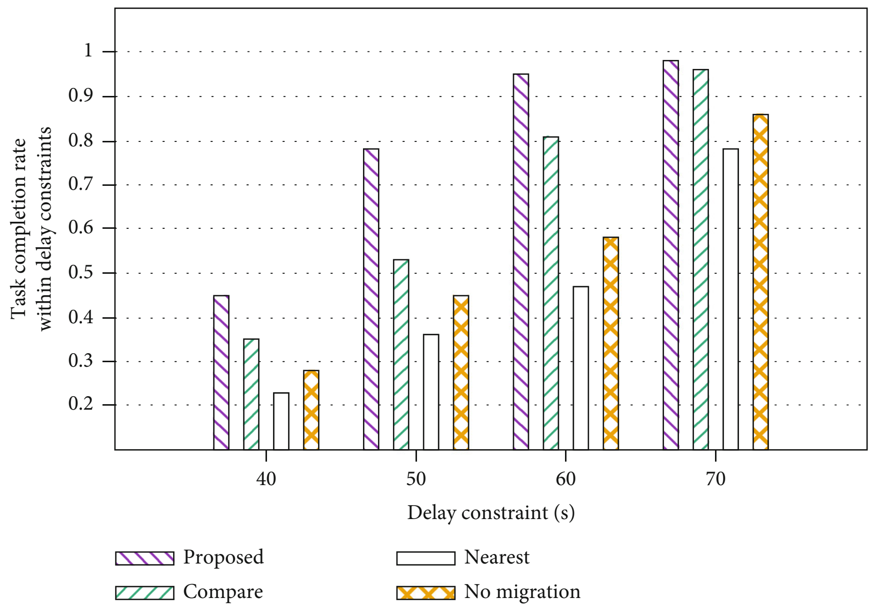


FIGURE 7: Comparison of the task completion rate for different delay constraints.

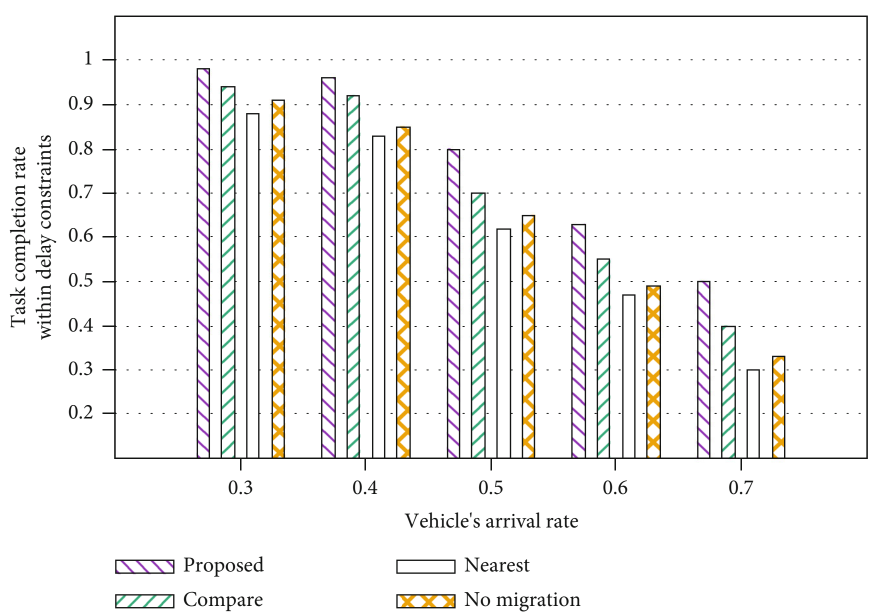


FIGURE 8: Comparison of the task completion rate for different arrival rates.

time modeled as an M/M/1 queuing system. The migration cost is also calculated by summing the response times of the current and target VECSs. In the *Nearest* algorithm, the computation task always migrates to the nearest VECS of the vehicle. In the *No Migration* algorithm, the computation task does not migrate to another VECS until the computation task is complete. Figures 5–9 show the degree of load balance and task completion rate within the delay constraints with varying arrival rates and mobility speeds.

Figure 5 depicts a comparison of the degree of load balance with respect to the arrival rate at a vehicle mobility speed of 20 m/s. The degree of load balance represents the deviation of the computing loads of the VECSs in Equation (9). The proposed algorithm performed approximately 23%, 39%, and 32% better than *Compare*, *Nearest*, and *No Migration*, respectively. The *Compare* algorithm focuses on the response time of VECSs, whereas the proposed algorithm focuses on the deviation of the VECS loads. The *Compare* algorithm tries to balance loads by lowering the average response time; the proposed algorithm attempts to balance loads by distributing computation tasks evenly among VECSs. Meanwhile, the *Nearest* algorithm selects the nearest VECS to a vehicle when it decides the target VECS. In this case, a small number of servers may experience workload

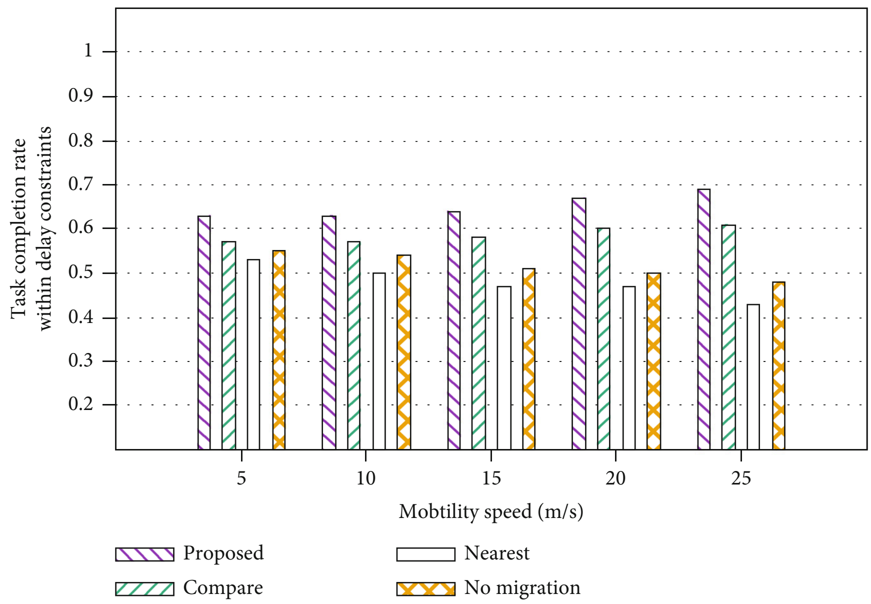


Figure 9: Comparison of the task completion rate for different mobility speeds.

concentration. Because the proposed algorithm considers the deviation of server loads when selecting the target VECS, congestion of certain VECSs can be avoided.

Figure 6 shows the degree of load balance with respect to the mobility speed of the vehicles at an arrival rate of 0.6. A higher mobility speed allows a vehicle to pass through the coverages of several VECSs within a certain period of time. From Figure 6, we can see that the degree of load balance for the proposed algorithm is almost constant regardless of the increase in speed. The proposed algorithm performs approximately 21%, 42%, and 35% better than *Compare*, *Nearest*, and *No Migration* algorithms, respectively. The *Compare* algorithm also shows a steady performance regardless of the speed. The *Nearest* and *No Migration* algorithms are sensitive to the increasing speeds.

In Figure 7, the rate of task completion within the delay constraint is shown for different values of delay constraint. The arrival rate and mobility speed are 0.6 and 20 m/s, respectively. The rate of task completion within the delay constraint is defined as the ratio of the number of completed tasks while satisfying the delay constraint to the total number of offloaded tasks. Figure 7 shows that the proposed algorithm has the highest task completion rate. Because overall load balancing is optimized, the computation time on the VECS is less than that when using other algorithms, and thus, the proposed algorithm achieves a relatively higher task completion rate.

Figures 8 and 9 show the performance in terms of the rate of task completion within the delay constraint with varying arrival rates and mobility speeds. In these simulations, we set the delay constraint to 50 s. Figure 8 shows that the proposed algorithm achieves approximately 14%, 25%, and 21% higher completion rates compared to the *Compare*, *Nearest*, and *No Migration* algorithms, respectively. As the arrival rate increases, regardless of how well the load balancing is performed, the latency increases because the number of computation requests handled by a VECS increases. In other words, as the workload of the VECS increases, the computing time of a task on the VECS increases, which degrades the performance. From the figure, we can see that despite the increase in the number of vehicles, the proposed algorithm is most optimized for load balancing, resulting in high task completion throughput. Because the workload is not biased to one VECS, the computation time and waiting time are lower.

Figure 9 shows that the proposed algorithm has better performance; the rate of task completion within delay constraints is approximately 13%, 28%, and 23% higher compared to those of *Compare*, *Nearest*, and *No Migration*, respectively. As the mobility speed increases, the proposed and *Compare* algorithms achieve a higher rate of completion. This is because the higher the mobility speed, the higher will be the migration decisions, which will result in a higher possibility of balancing loads among VECSs. However, the proposed algorithm balances the loads better than *Compare*; thus, the proposed algorithm achieves a higher rate of completion within the delay constraint.

## 5. Conclusions

In this study, we proposed a computation migration strategy using RL in VEC. To handle the high-dimensional state and action spaces, we proposed a deep RL-based migration strategy to optimize load balancing and migration cost while satisfying the delay constraints of computation tasks in a cooperative VECS group. We compared the proposed strategy with other strategies through simulations; the results showed that the proposed strategy achieves good load balancing among VECSs in terms of the number of computation requests.

This study considered a single agent in a multiuser environment. In future work, this can be expanded to multiagent

RL, each of which can be learned independently by the user [18]. In addition, various other factors can be considered, such as VECS group clustering [19] and load balancing with load prediction [20].

## Data Availability

The data used to support the findings of this study have not been made available, because our funding agency has not agreed to this.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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*Research Article*

# Energy-Efficient Distributed Packet Scheduling Optimization Strategy in Cooperative Vehicle Infrastructure Systems

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In the cooperative vehicle infrastructure system (CVIS), due to the limitation of deployment conditions, some roadside units (RSUs) need to use renewable energy to supply power and transmit the fused sensor network's data to the backbone network through the passing vehicles. Aiming at the problem of energy consumption and time delay guarantee of multiple self-powered RSUs in the CVIS, a distributed packet scheduling optimization strategy for energy-delay trade-off in self-powered RSUs is proposed. The strategy can minimize the system energy consumption by constraining the packet queue length of the self-powered RSUs. A dynamic optimization model of distributed packet adaptive scheduling for multiple self-powered RSUs is established based on the Lyapunov optimization theory. Based on the knapsack algorithm, the analytical algorithm of the optimization model is proposed. The simulation results show that the packet scheduling strategy can reduce the energy consumption and delay of the system by satisfying the upper limit of the packet queue length.

## 1. Introduction

*1.1. Motivation.* The highway has the characteristics of long distance, small traffic density, relatively stable vehicle route, and moving speed, which is an important scene for the research and application of Internet of Vehicles [1, 2]. In the cooperative vehicle infrastructure system (CVIS), some highway roadside units (RSUs) deployed in remote mountainous areas, grassland forest belts, and Gobi Desert cannot directly access the system backbone network and power supply grid. In order to ensure the continuous operation of the equipment and real-time communication of data acquisition, it is necessary to maintain the power supply of renewable energy acquisition such as solar energy and wind energy through energy harvesting [3]. Data transmission is completed in the way of "store-carry-forward" through passing vehicles within its wireless coverage [4–6]. These RSUs not only are important network access equipment to provide information services for vehicles on highways but also serve as gateway nodes of sensor networks for the surrounding environmental monitoring (traffic conditions, natural disasters, and animal activity information) and undertake the function of transmitting monitoring data to roadside units connected with the Internet [7].

In the above scenario, the utilization efficiency of external energy harvesting and the guarantee of monitoring data transmission efficiency are the most important issues when dealing with the distributed packet scheduling optimization of each self-powered RSUs in the CVIS. The monitoring data collected by the RSUs through the wireless sensor network needs to be sent to the RSUs connected to the Internet through the passing vehicles' relay. In order to ensure the timeliness of monitoring data, it is necessary to ensure the stability and efficiency of data transmission. Because the highway section is relatively long, it is assumed that under the condition of constant speed of vehicles, the fast vehicles will surpass the slow ones in the process of driving. Therefore, when the speed of vehicles reaching the coverage area of roadside units is slow, the RSUs should choose to send fewer packets to the vehicles or continue to wait until the faster vehicles arrive and then send the packets to the vehicles for relaying transmission. For faster vehicles, the packets should be transferred to the vehicle as much as possible to reduce the queue length of RSUs' packet buffer. In this way, the system can reduce the waste of excess energy caused by transferring packets to slower vehicles. When the amount of RSU's data collection per unit time is fixed, the reduction of RSU's packet queue length reflects the improvement of transmission efficiency and the reduction of packet transmission delay [8]. Therefore, the main problem of this paper is to minimize the energy consumption of RSUs under the condition of low queuing delay and find the best trade-off point between energy consumption and delay.

*1.2. Related Works.* As mentioned in references [9, 10], the high-speed mobility of vehicles and the imbalance of vehicle distribution make the topology of vehicular networks change frequently. In reference [9], the vehicular sensing network-aided smart city model was constructed and its application in public service and urban flow management was evaluated. Then, the information source selection algorithm of the complex network and the sharing mechanism of urban information based on reinforcement learning were considered and a series of open challenges is also complemented. In reference [10], the weighted undirected graph model of Internet of Vehicles (IoV) sensing networks was established and the real taxi GPS dataset was used to verify its time invariant complex characteristics. In addition, the authors proposed an IOV-assisted local traffic information collection architecture, a sink node selection scheme for information influx, and an optimal traffic information transmission scheme. In order to improve the network access opportunities of vehicles, RSUs are deployed along the road. However, in some remote areas, the RSUs cannot be connected to the power system, so they can only operate by the way of external energy harvesting. According to the data of the U.S. Department of Transportation, it is estimated that 40% of the RSUs on highways will use energy harvesting to realize the self-powered supply through solar energy or wind energy harvesting equipment [11] and make corresponding scheduling according to the communication conditions and energy storage status of the system, so as to improve the system on the premise of ensuring the service life of RSUs' batteries The energy efficiency can improve the performance of the CVIS.

Atallah et al. summarizes the application of renewable energy and energy harvesting technology in the field of Internet of Vehicles. By discussing the feasibility of introducing energy harvesting technology into the application of Internet of Vehicles, this paper puts forward the open research problems and directions to be solved in this field [3]. In reference [12], RSUs with self-powered function was designed to optimize the service capacity of the RSU under multiple time scales and the conditions for the system energy to reach the balance of supply and demand were studied. Ku et al. studied self-powered RSUs that can provide edge computing for Internet of Vehicles. Aiming at the energy consumption minimization problem of RSUs and space-time energy balance problem, a control algorithm combining energy consumption and service performance balance is proposed to minimize QoS loss under the constraint of task delay [13]. Patra and Murthy proposed a decision-making method combining RSU deployment and dormant scheduling for self-powered RSUs with solar energy as the main energy collection source. The decision-making method combined with free flow vehicles and their speed distribution transformed the problem of RSUs' deployment interval optimization into work-sleep scheduling of RSUs to achieve the function of energy saving [14]. Nikookaran et al. studied the problem of RSUs' deployment to minimize the sum of capital and operation costs. In the literature, historical vehicle traffic tracks and a group of alternative deployment locations were sampled on highways to calculate the minimum deployment cost of RSUs. The study suggested that under specific conditions, more solar energy self-powered RSUs should be deployed on highways [15]. Khezrian et al. studied the energy efficient downlink traffic scheduling optimization of multiple self-powered RSUs working together. By balancing the load energy consumption of each RSU, the energy consumption of the whole RSU system was balanced, which played a role in reducing consumption and increasing efficiency [16]. Atallah et al. studied the periodic charging self-powered RSUs based on reinforcement learning. Through the energy-saving adaptive scheduling protocol, the downstream traffic scheduling of RSU was optimized to maximize the number of service requests satisfied by rechargeable batteries of RSU in a discharge cycle [17]. Atoui et al. studied the downlink communication scheduling problem of self-powered RSUs. According to the energy state of the RSUs, the power was adjusted and the vehicles with different distances were selected to provide services and the number of service vehicles was maximized [18]. In reference [19], aiming at the energy efficiency problem of RSUs, under the condition that the energy of vehicles is not constrained, a scheduling method combining RSUs and relaying transmission of passing vehicles with multihop data forwarding is proposed, so as to reduce the energy consumption of RSUs. Hammad et al. studied the energy-saving scheduling problem of RSUs with variable bit rate transmission between RSUs and vehicles, obtained the lower limit of energy consumption to meet the demand of different vehicles' service volume, and designed the optimal offline variable bit rate slot scheduling algorithm of RSUs [20]. In reference [21–23], Ali et al. describes the "Green Vehicular Ad hoc Network (GVANET)" project, which is aimed at realizing the self-powered RSUs with reasonable cost, reliability, safety, and easy installation. At the equipment level, the project designs RSU's architecture for different fault events to ensure robustness. At the system level, the project designs a RSU system with strong sustainability, safety, reliability, and scalability.

*1.3. Problem Statement and Novel Contributions.* From the summary and analysis of the relevant research, it can be seen that at this stage, the main research topic based on the self-powered RSUs focuses on solving the problem of ensuring the data transmission accessibility of the RSU under the energy constraint, while the performance of the data communication network composed of all RSUs and packet-carrying vehicles on the whole road is less considered. In this paper, we research the network performance requirements of minimizing the energy consumption of the self-powered RSUs and optimizing the service in the communication scenario between RSUs based on multigroup vehicles with relay under the background of the CVIS. In view of the trade-off between energy consumption and delay, the system dynamically adjusts the vehicles' speed selection range and the number of packets to be sent according to RSUs' packet queue length, which can reduce the transmission delay and energy consumption of self-powered RSUs. Specifically, according to the queue length of RSUs and the speed of vehicles passing by, the packet scheduling decision is made. Through the establishment of the optimization model, the optimization problem is analyzed and the optimal strategy is solved. The optimization problem is transformed by the Lyapunov function and analyzed through the structure of the optimal solution.

## 2. System Model

The environment monitoring data transmission scenario of the self-powered RSUs using passing vehicles' relaying in the in the CVIS studied in this paper is shown in Figure 1. $N$ RSUs : $\mathrm{RSU}_1, \cdots, \mathrm{RSU}_n, \cdots, \mathrm{RSU}_N$ are deployed on specific sections of the highway. Each RSU cannot be connected to the power grid and the Internet, so it is necessary to realize self-powered supply through energy harvesting technology to ensure the continuous work of the system. All vehicles passing through the coverage of RSUs can be used as mobile sinks to carry out data packet transmission and forward the packets to the RSU connected to the backbone network, so as to realize the data communication between isolated self-powered RSUs and environment monitoring data center.

*2.1. Packet Scheduling Model of Self-Powered RSUs.* The distributed packet scheduling model between the self-powered RSUs and the passing vehicles is shown in Figure 2. On this road section, there are $N$ self-powered RSUs, harvesting renewable energy from the outside and storing them in their energy queue. Since the goal of this paper is to minimize energy consumption, the system needs to ensure that the energy is sufficient and will not be exhausted. The environmental monitoring data is stored in the data cache of RSUs, waiting to be sent in the form of packet queuing.

In order to describe the working process of the system conveniently, we set it as a discrete time system. In a certain time slot, if no vehicle passes through the RSU, the data packets of the RSU will be queued in its cache. If there are vehicles arriving at the RSU in the slot, the vehicle speed status $V_n[t]$ and packet queue status $Q_n[t]$ will be combined according to the packet scheduling strategy to determine whether to send packets to the vehicle and the duration of sending packets $\xi_n[t]$, so as to control the energy consumption and delay of the system. Finally, the packet-carrying vehicle will forward the data to the destination RSU connected with the Internet and then transmit the packet to the environment monitoring data center.

*2.2. Vehicles' Speed State Model.* Under the condition of free flow speed, the arrival time of vehicles obeys Poisson distribution with parameter $\mu$ and the time interval $T$ between two vehicles arriving at $\mathrm{RSU}_n$ successively obeys negative exponential distribution. Its probability density function is $f(t) = \mu e^{-\mu t}, t > 0$ and the probability distribution function is $F(t) = P(T \le t) = 1 - e^{-\mu t}, t > 0$. If the system time slot length is expressed by $\tau$, then the probability that at least one vehicle will arrive in $\tau$ is as follows:

$$P_a = P(T \le \tau) = 1 - e^{-\mu\tau}, \quad \tau > 0. \tag{1}$$

Defining $t$ as the slot number, $t = \{0, 1 \cdots T\}$ and $v_n[t]($ $v[t] \ge 0)$ is the speed status of the vehicle arriving at $\mathrm{RSU}_n$ in the slot $t$. In particular, $v_n[t] = 0$ means that no vehicle passes through $\mathrm{RSU}_n$ in time slot $t$.

It is assumed that the vehicle speed remains unchanged during the driving between RSUs and the vehicle speed is independently and identically distributed for each time slot. In the free flow velocity model, the probability density function of vehicle speed $v$ follows the Gaussian distribution of mean value $\bar{V}$ and standard deviation $\sigma$. It is shown as follows:

$$f(v)^* = \frac{1}{\sigma\sqrt{2\pi}} e^{\left[-\left(v-\bar{V}/\sigma\sqrt{2}\right)^2\right]}. \tag{2}$$

Because of $v \in [V_{\min}, V_{\max}]$, the truncated probability density function of vehicle speed distribution can be expressed as follows:

$$f(v) = \frac{2f(v)^*}{\operatorname{erf}\left(V_{\max} - \bar{V}/\sigma\sqrt{2}\right) - \operatorname{erf}\left(V_{\min} - \bar{V}/\sigma\sqrt{2}\right)}. \tag{3}$$

*2.3. Packet Scheduling Model.* In the application scenario described in this paper, the speed of passing vehicles directly affects the packet scheduling time between RSU and vehicles, and the packet cache queue directly affects the work efficiency of the system. Therefore, the energy-delay trade-off distributed optimization strategy of packet scheduling proposed in this paper needs to start from two aspects: packet cache queue length and vehicle speed.

According to the above, the system should be modeled as a discrete time system and the slot length is $t'$. However, in the in the CVIS of the highway, the vehicle can only establish communication connection with RSU within whose coverage. When the vehicle drives out of the coverage of $\mathrm{RSU}_n$, the communication will be disconnected. Until the vehicle enters the coverage of the next RSU, the vehicle can reestablish the connection with the RSU. Therefore, there are two communication states of on/off between vehicles and RSUs, which represent the working state and offline state between vehicles and RSUs.

Therefore, it is necessary to redefine the time slot length of the system as shown in Figure 3. The vehicles' arrival obeys the Poisson distribution with parameter $\mu$. Therefore, it is assumed that the probability of establishing wireless

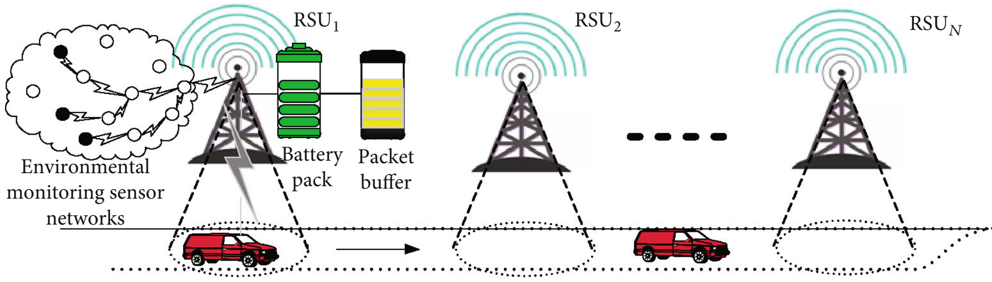


FIGURE 1: Schematic diagram of monitoring data transmission scene of self-powered RSUs.

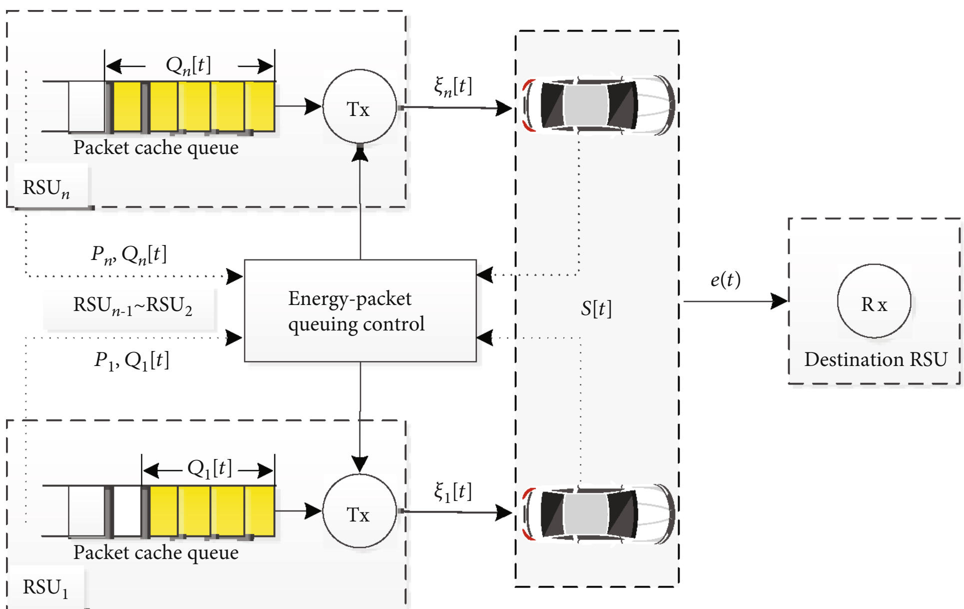


FIGURE 2: Data packet scheduling process model between self-powered RSUs and passing vehicles.

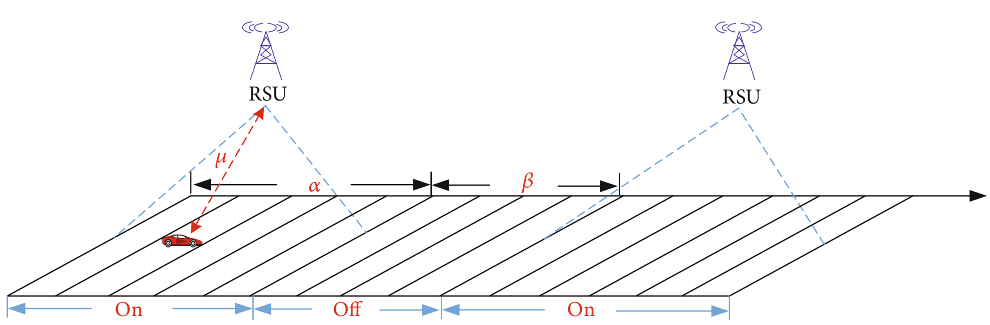


FIGURE 3: Interrupted Bernoulli process of the CVIS application scenario.

communication connection between the vehicles and $RSU_n$ follows the interrupted Bernoulli process (IBP) with parameter $(\mu, \alpha, \beta)$. Among them, in the whole process of vehicles' relaying, the time occupied by the working state and offline state obeys the geometric distribution and the time of the two modes accounts for $\alpha$ and $\beta$ of the total time, respectively. Therefore, the discrete slot length $\tau$ in the on/off mode is redefined as follows:

$$\tau = \frac{t'\alpha}{\alpha + \beta}. \tag{4}$$

Because the number of vehicles under the coverage of RSUs is one of the important parameters to calculate the energy consumption of the system, it is necessary to establish a simple free flow model of traffic. By analyzing the vehicle distribution characteristics of the model, the number of vehicles in each time slot within the coverage of RSU $S[t]$ can be obtained.

The length of the road section considered in this paper is defined as $L$. According to the previous description, the average speed of vehicles under the speed limit of the highway is $\bar{V}$, while in the simple traffic free flow model, the default vehicle speed remains unchanged. Therefore, the cumulative distribution function of the vehicle's dwell time on this road section is as follows [24]:

$$F_r(\Delta t) = 1 - F\left(\frac{L}{\Delta t}\right) = 1 - \frac{1 + \operatorname{erf}\left(\left((L/\Delta t) - \bar{V}\right)/\sigma\sqrt{2}\right)}{\operatorname{erf}\left(\left(V_{\max} - \bar{V}\right)/\sigma\sqrt{2}\right) - \operatorname{erf}\left(\left(V_{\min} - \bar{V}\right)/\sigma\sqrt{2}\right)}, \quad (5)$$

where $F(L/\Delta t)$ is the probability distribution function corresponding to equation (3). According to $F_r(\Delta t)$, the probability $P_n(t)$ of the number of vehicles $S[t] = n$ covered by RSU in time slot $t$ can be deduced.

Since the arrival of vehicles obeys the Poisson distribution with parameter $\mu$, the probability of $k$ vehicles on this road section in the time interval of $(0, t)$ is expressed as follows:

$$a_k(t) = \frac{(\mu t)^k e^{-(\mu t)}}{k!}. \quad (6)$$

In equation (5), in slot $t$, the probability that any vehicle on the road section has arrived in slot $t_i$ is $1 - F_r(t - t_i)$. Since the arrival of vehicles follows Poisson distribution, the distribution of vehicle arrival time with $k$ vehicles arriving within the time interval of $(0, t)$ is equivalent to the uniform distribution of $k$ points in the range of $(0, t)$. Therefore, the probability $P_k(t)$ of the existence of any $k$ vehicles on the road section within time slot $t$ is as follows:

$$P_k(t) = \int_0^t [1 - F_r(t - t_i)] \frac{dt_i}{t} = \frac{1}{t}\int_0^t [1 - F_r(t_i)] dt_i. \quad (7)$$

Therefore, the probability of opposite events of this event is as follows:

$$1 - P_k(t) = \frac{1}{t}\int_0^t F_r(t_i) dt_i. \quad (8)$$

Since the probability of an event with $n$ vehicle running on the road section obeys binomial distribution under the condition that $k$ vehicles arrive at the section within the time interval of $(0, t)$, the probability of the event can be deduced from equations (7) and (8).

$$P_{n|k}(t) = \begin{cases} C_k^n [P_k(t)]^n [1 - P_k(t)]^{k-n}, & n \le k, \\ 0, & n > k. \end{cases} \quad (9)$$

It is known that the probability of establishing communication connection between the vehicle and $\mathrm{RSU}_n$ follows the IBP with parameter $(\mu, \alpha, \beta)$. The probability of $k$ vehicles in the coverage of RSU in the $t$th slot can be deduced by synthesizing equations (6) and (9).

$$P(S[t] = k) = \frac{\alpha}{\alpha + \beta}\sum_{k=n}^{\infty} C_k^n [P_k(t)]^n [1 - P_k(t)]^{k-n} \cdot \frac{(\mu t)^k e^{-\mu t}}{k!} = \frac{\alpha[\mu t \cdot P_k(t)]^n e^{-\mu t \cdot P_k(t)}}{(\alpha + \beta) n!}. \quad (10)$$

In order to ensure the low delay of the packet forwarding, effectively reduce the energy consumption of the system and the self-powered RSUs needs to determine the duration of sending packets $\xi_n[t]$ to the vehicles according to the different speed states. If the speed of the passing vehicle is faster, the corresponding $\mathrm{RSU}_n$ packet transmission time $\xi_n[t]$ of $\mathrm{RSU}_n$ should be larger; conversely, if the speed of the passing vehicle is slow, $\mathrm{RSU}_n$ should reduce the packet transmission time accordingly.

Firstly, we defined the packet transmission duration vector as $\xi[t] = \{\xi_1[t], \cdots, \xi_n[t]\}$ and the number of packets transmitted by $\mathrm{RSU}_n$ in unit time as $R_n$. Therefore, the number of packets transmitted by $\mathrm{RSU}_n$ in time slot $t$ is known as $D_n[t] = R_n \xi_n[t]$. Since the number of queued packets $Q_n[t]$ in the packet queue is limited in time slot $t$, the relationship between the number of packets queued and packets forwarded should be met as follows:

$$Q_n[t] \ge R_n \xi_n[t], \quad \forall n \in N. \quad (11)$$

Secondly, the speed status of passing vehicles directly affects the duration of packet forwarding $\xi_n[t]$. The faster the speed is, the longer the packet transmission duration is, and the duration should not exceed the slot length $\tau$. Therefore, $\xi_n[t]$ needs to satisfy the following relationship:

$$\xi_n[t] = \begin{cases} \tau P\{\xi_n[t] = \tau | v_n[t] = m, A_n[t] = a, Q_n[t-1] = q\}, 1 \le m \le M, \\ 0, \quad m = M + 1, \end{cases} \quad (12)$$

where $a = \{0, 1\}$, $0 \le q \le Q$. According to equations (11) and (12), the following relationship is obtained:

$$0 \le \xi_n[t] \le T_n[t], \quad \forall n \in N, \quad (13)$$

where $T_n[t] = \min\{(Q_n[t])/R_n, \tau\}$.

Finally, considering the packet forwarding states of all RSUs in the CVIS, the overall packet forwarding duration

$\xi_n[t]$ of the system should meet the following conditions:

$$\sum_{n=1}^{i} \xi_n[t] \le S[t]\tau, \quad 1 \le i \le N. \tag{14}$$

*2.4. Packet Queue Model of RSUs.* Let $Q_n[t+1]$ denote the queue length of RSU$_n$'s packet cache in time slot $t+1$, and its state update expression is as follows:

$$Q_n[t+1] = \max\{Q_n[t] - D_n[t], 0\} + A_n[t]. \tag{15}$$

Because the packet queue length in RSU directly represents the efficiency of the system, the packet queue length of RSU is at a low level while reducing the transmission delay of the system. Therefore, in order to ensure the low delay of the system, it is necessary to set an upper bound value $\varepsilon$ of the packet queue length to control the average queue length $q_n$ of RSU. Therefore, the expression of the average packet queue length is as follows:

$$q_n = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathrm{E}\{Q_n[t]\} < \varepsilon, \quad \exists\varepsilon \in \mathfrak{R}^+. \tag{16}$$

*2.5. Energy Consumption Model of the CVIS.* Under the condition that the packet transmission power $P_n$ of each RSU$_n$ is known, the duration $\xi_n[t]$ of each RSU sending packets to passing vehicles in each time slot can be deduced. Thus, the energy consumption of each RSU due to packet transmission in time slot $t$ is obtained. The expression of total energy consumption $e(t)$ of packet transmission in slot $t$ in the whole CVIS is as follows:

$$e(t) = \sum_{n=1}^{i} P_n \xi_n[t], \quad 1 \le i \le N. \tag{17}$$

However, the number of vehicles passing through RSU and its speed state are dynamic. Therefore, it is more scientific to analyze the average energy consumption of the CVIS under a long-term operation. The expression of long-term average energy consumption of the system is as follows:

$$e = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} E\{e(t)\}. \tag{18}$$

## 3. Optimization Problem

From the discussion in the previous section, keeping the packet queue length of the system at a low state reflects the efficiency of the CVIS. Therefore, the packet scheduling optimization strategy proposed in this paper needs to control the packet transmission time of RSUs by the speed of the relaying vehicles.

The optimization goal is to minimize the total energy consumption of the CVIS, reduce the packet backlog as much as possible, and improve the packet transmission efficiency while reducing the queuing delay of the system. However, due to the stochasticity of the speed status of each vehicle within the coverage of self-powered RSUs, if the system only waits for the fastest vehicle for packet transmission, although the energy consumption will be minimized, many packets will be overstocked, which directly reduces the work efficiency of the system. Therefore, there is a trade-off relationship between the energy consumption and the queue length of RSUs' packet cache. The optimization problem proposed in this paper coordinates the relationship between the energy and the delay and solves the trade-off between energy consumption and work efficiency of the CVIS. The optimization model is as follows:

$$\begin{gathered} \min_{\xi(t)} e = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} E\{e(t)\}, \\ \text{s.t.} \begin{cases} 0 \le \xi_n[t] \le T_n[t], & 1 \le n \le N, \\ \sum_{n=1}^{i} \xi_n[t] \le S[t]\bullet\tau, & 0 < i < N, \\ q_n = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} E\{Q_n[t]\} < \varepsilon, & \exists\varepsilon \in \mathfrak{R}^+. \end{cases} \end{gathered} \tag{19}$$

Due to the stochasticity of packet's arrival state and vehicles' speed in optimization problem (19), it is difficult to predict and analyze each state of the system through offline data statistics. In this scenario, the state space is huge and the online optimization scheme of optimization problem (19) has high computational complexity, so it is necessary to transform the problem (19) accordingly to reduce its computational complexity.

*3.1. Lyapunov Optimization and Model Transformation.* In this paper, we can use the Lyapunov optimization theory to transform the model, reduce the computational complexity of the model, so as to reflect the trade-off relationship between energy and packet queuing in a more intuitive way, and simplify the constraints.

Firstly, the vector matrix $\boldsymbol{\theta}(\mathbf{t})$ of each RSU$_n$ packet queue length state $Q_n[t]$ is defined and the Lyapunov function is defined by $\boldsymbol{\theta}(\mathbf{t})$ as follows:

$$L(\boldsymbol{\theta}(\mathbf{t})) = \frac{1}{2}\sum_{n=1}^{N} Q_n^2[t]. \tag{20}$$

Therefore, the packet queuing state in each RSU is transformed into the form of equation (20). If the value of $L(\boldsymbol{\theta}(\mathbf{t}))$ is large, it indicates that at least one RSU has a large packet backlog; if the value of $L(\boldsymbol{\theta}(\mathbf{t}))$ is small, the packet backlog in each RSU is small. Therefore, reducing the value of $L(\boldsymbol{\theta}(\mathbf{t}))$ can directly reduce the overall packet queue length of the system. The Lyapunov drift $\Delta(\boldsymbol{\theta}(\mathbf{t}))$ can be obtained as follows:

$$\Delta(\boldsymbol{\theta}(\mathbf{t})) = E\{L(\boldsymbol{\theta}(\mathbf{t}+1)) - L(\boldsymbol{\theta}(\mathbf{t})) \mid \boldsymbol{\theta}(\mathbf{t})\}. \tag{21}$$

Since the system optimization problem should reflect the trade-off relationship between energy consumption and packet queue length, energy should be added as a drift component in equation (21), so the redefined Lyapunov drift is expressed as follows:

$$\Delta(\boldsymbol{\theta}(\mathbf{t})) + VE\{e(t) \mid \boldsymbol{\theta}(\mathbf{t})\}, \tag{22}$$

where $V > 0$. As a parameter to coordinate the trade-off between the packet queue length and the energy consumption, the larger the value of $V$, the greater the weight of energy consumption in the Lyapunov drift parameter, the greater the impact on the system drift. Therefore, the system can be optimized by adjusting the value of $V$. The upper bound of Lyapunov is deduced to optimize the system.

According to the theorem, there is $\{\max[(a-b), 0]\}^2 \le a^2 + b^2 - 2ab$ for $\forall a, b \ge 0$, so equation (15) can be transformed into the following expression:

$$Q_n[t+1]^2 \le Q_n[t]^2 + A_n[t]^2 + D_n{}^2[t] - 2Q_n[t]D_n[t] + 2\max\{Q_n[t] - D_n[t], 0\}. \tag{23}$$

Since the size relationship between the queue length of RSU$_n$'s packets $Q_n[t]$ and the number of packets that can be sent $D_n[t]$ is uncertain, let $D_n[t]'$ denote the number of packets actually sent by RSU$_n$ to passing vehicles in slot $t$ as follows:

$$D_n[t]' = \begin{cases} D_n[t], & Q_n[t] \ge D_n[t], \\ Q_n[t], & \text{else}. \end{cases} \tag{24}$$

From equation (24), it can be concluded that

$$\max\{Q_n[t] - D_n[t], 0\} = Q_n[t] - D_n[t]'. \tag{25}$$

Using equations (23) and (25), the following relationship can be derived:

$$Q_n[t+1]^2 - Q_n[t]^2 \le A_n[t]^2 + D_n{}^2[t] + 2Q_n[t](A_n[t] - D_n[1]) - 2A_n[t]D_n[t]'. \tag{26}$$

Since $2A_n[t]D_n[t]' \ge 0$, the term does not affect the inequality of equation (26) and the inequality can be simplified by omitting this term. Therefore, inequality (25) can be transformed into the following expression:

$$\frac{1}{2}\left(Q_n[t+1]^2 - Q_n[t]^2\right) \le \frac{1}{2}\left(A_n[t]^2 + D_n{}^2[t]\right) + Q_n[t](A_n[t] - D_n[t]). \tag{27}$$

According to the relationship between equations (20), (21), and (27), we can get that the packet queue length of all RSUs in the system satisfies the following relationship:

$$\Delta(\boldsymbol{\theta}(\mathbf{t})) \le \frac{1}{2}\sum_{n=1}^{N} E\left\{A_n[t]^2 + D_n[t]^2 \middle| \boldsymbol{\theta}(\mathbf{t})\right\} + \sum_{n=1}^{N} Q_n[t]E\{A_n[t] - D_n[t] \mid \boldsymbol{\theta}(\mathbf{t})\}. \tag{28}$$

Let $A_n^{\max}$ be the maximum value of $A_n[t]$ and $R_n^{\max}$ the maximum value of $R_n$. Therefore, the right terms in equation (28) satisfy the following relation:

$$D_n[t] = R_n\xi[t] \le R_n^{\max}, \tag{29}$$

$$\sum_{n=1}^{N} E\left\{A_n[t]^2 + D_n[t]^2 \mid \boldsymbol{\theta}(\mathbf{t})\right\} \le \sum_{n=1}^{N}\left[(A_n^{\max})^2 + (R_n^{\max})^2\right]. \tag{30}$$

Let the parameter $C = (1/2)N[(A_n^{\max})^2 + (R_n^{\max})^2]$ and bring it into equation (28). The Lyapunov drift function described in equation (22) satisfies the following inequality relationship:

$$\Delta(\boldsymbol{\theta}(\mathbf{t})) + VE\{e(t) \mid \boldsymbol{\theta}(\mathbf{t})\} \le C + \sum_{n=1}^{N} Q_n[t]E\{A_n[t] - D_n[t] \mid \boldsymbol{\theta}(\mathbf{t})\} + VE\{P_n\xi_n[t] \mid \boldsymbol{\theta}(\mathbf{t})\}. \tag{31}$$

The right part of inequality (31) is the upper bound of the Lyapunov drift function. By minimizing the upper bound, we can adjust the packet transmission duration $\xi_n[t]$ to obtain the optimal critical point of the optimization model. Therefore, the optimization model of the system is further transformed into the following expressions:

$$\min_{\xi[t]}\left\{C + \sum_{n=1}^{N} Q_n[t]\{A_n[t] - R_n[t]\xi_n[t]\} + V\sum_{n=1}^{N} P_n\xi_n[t]\right\}, \tag{32}$$

where $C$ and $A_n[t]$ are constants in unit time, which do not affect the system optimization results, so they can be ignored, so equation (29) can be simplified as follows:

$$\min_{\xi[t]} \sum_{n=1}^{N}\{VP_n - Q_n[t]R_n\}\xi_n[t]. \tag{33}$$

Let $\sigma_n[t] = Q_n[t]R_n - VP_n$, and bring it into equation (33) to get the final system optimization model:

$$\begin{gathered} \max_{\xi[t]} \sum_{n=1}^{N} \sigma_n[t]\xi_n[t], \\ \text{s.t.}\begin{cases} 0 \le \xi_n[t] \le T_n[t], \quad 1 \le n \le N, \\ \sum_{n=1}^{N} \xi_n[t] \le S[t]\bullet\tau. \end{cases} \end{gathered} \tag{34}$$

In this paper, the proposed distributed energy-delay trade-off packet scheduling optimization strategy based on the Lyapunov optimization theory only needs to observe the backlog of all queues (packets queue and energy queue) and make corresponding decisions on the status of RSUs and passing vehicles. Therefore, the complexity of the algorithm is linear with the number of RSUs $N$, which is easy to realize.

Table 1: Simulation parameters.

| Parameter | Symbol | Value | Unit |
|---|---|---|---|
| Length of expressway | $L$ | 10 | Kilometer |
| Number of RSU$_S$ | $N$ | 10 | / |
| Coverage radius of RSUs | $R$ | 250 | Meter |
| Speed limit | $[V_{min}, V_{max}]$ | [16.67, 33.33] | Meter/second |
| Speed expectation | $\bar{V}$ | 25 | Meter/second |
| Speed standard deviation | $\sigma$ | 5.56 | / |
| Vehicle arrival rate | $\mu$ | 0.55 | Vehicles/second |
| Slot length | $t'$ | 1 | Second |
| Loop count | $t$ | 1500 | / |

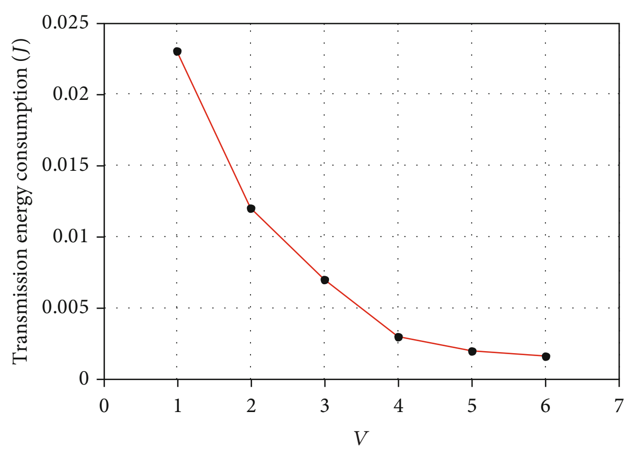


Figure 4: Trend of energy consumption changing with weight.

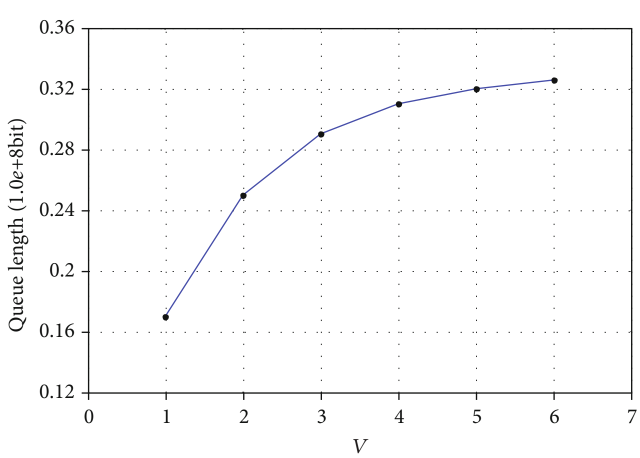


Figure 5: Trend of packet queue length changing with weight.

*3.2. Analytical Algorithm of Optimization Problem.* It can be seen from the model derived in the previous section that the optimization process of the system model can be analogized to maximize the value of the system in the limited resource space. The constraint of the optimization model is the resource space, and the output value of the model is the embodiment of the system value. Therefore, the model can be transformed into a knapsack problem to solve [25].

The parameter $\sigma_n[t]$ of the system optimization model represents the system value. First, the system needs to sort the values of $\sigma_n[t]$ in a descending order. Secondly, the ordered $\sigma_n[t]$ is put into the limited resource space in order, that is, "backpack." The key of the knapsack problem analysis is to find the break point of the process. Therefore, through the known interruption conditions of knapsack problem, the following is found:

(i) The remaining resource space is empty

(ii) The value of the "items" put into the "knapsack" is negative

Once the optimal break point of the knapsack problem is obtained, the optimal packet transmission duration $\xi_n^*[t]$ of the system can be deduced.

In order to obtain the optimal break point, $\Upsilon$ is defined as the interruption index of the knapsack problem and $\Upsilon = \min\{\gamma_1, \gamma_2\}$, where $\gamma_1, \gamma_2$ satisfies the following relationship:

$$\begin{cases} \gamma_1 = \underset{n}{\operatorname{argmin}} \sum_{m=1}^{n} T_m[t] > S[t] \bullet \tau, \\ \gamma_2 = \arg \underset{n}{\max} \sigma_n[t] \geq 0. \end{cases} \tag{35}$$

Therefore, the optimal packet transmission duration $\xi_n^*[t]$ is expressed as follows:

$$\xi_n^*(t) = \begin{cases} T_n[t], & n < \Upsilon, \\ \min\left\{ S[t]\tau - \sum_{n=1}^{\Upsilon-1} T_n[t], T_\Upsilon[t] \right\}, & n = \Upsilon, \\ 0, & \text{else}. \end{cases} \tag{36}$$

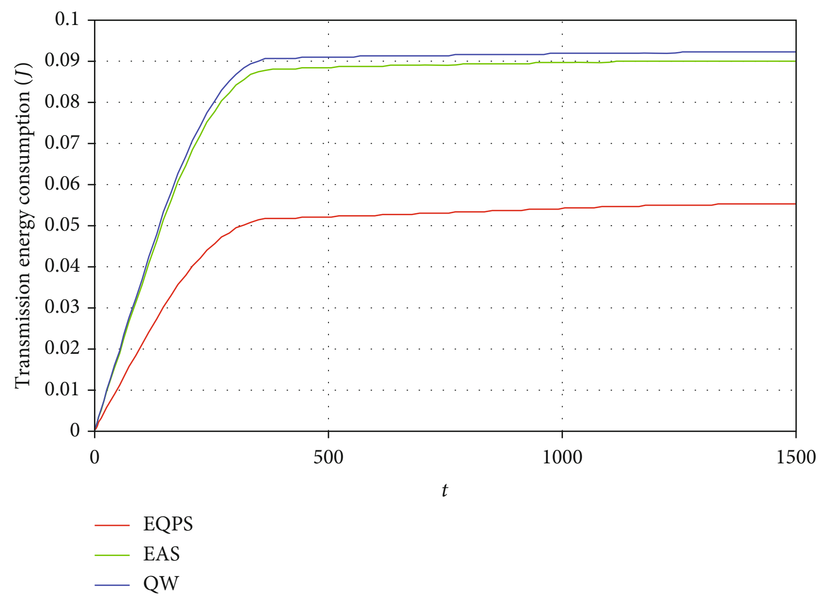


Figure 6: Comparison of system energy consumption simulation under different strategies.

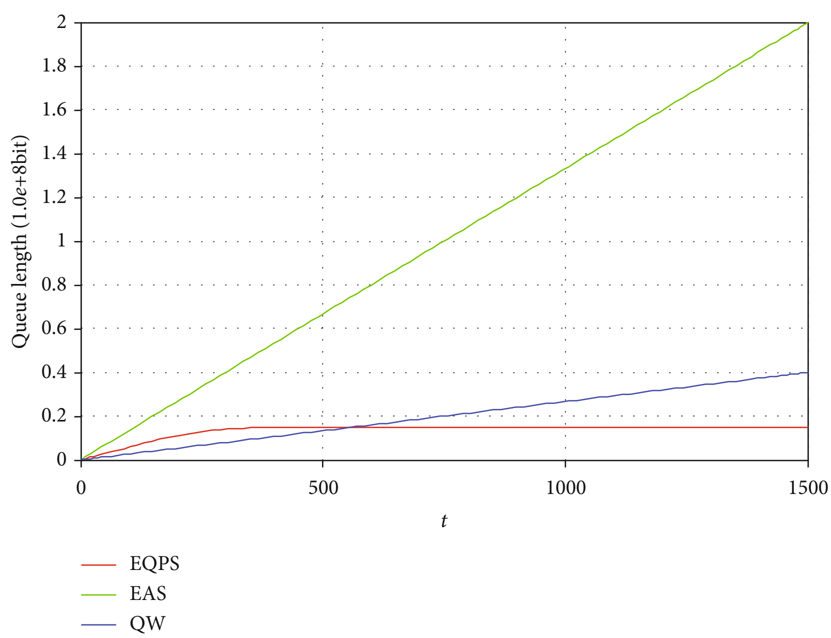


Figure 7: Comparison of packet queue length simulation under different strategies.

## 4. Simulation and Analysis

Aiming at the energy-efficient distributed packet scheduling optimization strategy (EQPS) proposed in this chapter, the following two parts of simulation experiments are carried out by using the simulation software MATLAB:

(i) According to the system optimization model, the trend of system energy consumption and packet queuing with weight coefficient is drawn

(ii) Under the same simulation parameters, this strategy model and the two commonly used baseline models are compared and analyzed in terms of energy consumption and packet queuing

The basic parameters of simulation are as shown in Table 1:

In this scenario, the packet arrival rate and transmission power of RSU are uniformly distributed: $A_n[t] \sim U[0, 2000]$ bits/s, $P_n \sim U[10,200]$ mW, so the packet transmission rate of RSU is $R_n \in [1330, 1760]$ bits/s.

The two baseline models are equal allocation strategy (EAS) and queue-weighted strategy (QW). Among them, the EAS means that the system allocates the equal packet transmission duration to all passing vehicles connected with the RSUs. The QW means that the system determines the weight of the duration of packet transmission with vehicles according to the backlog of packets in RSU. In other words, the larger the backlog of RSU packets is, the greater the weight is, and the longer the packet transmission duration is.

The performance simulation results of EQPS proposed in this paper are shown in Figures 4 and 5, where Figure 4 shows the trend of energy consumption per time slot with the increase of weight $V$. The simulation results show that the overall energy consumption of the system decreases with the increase of weight $V$. The reason is that with the increase of weight, the impact of energy consumption on system performance increases, so the system will adaptively reduce energy consumption to balance the overall performance of the system. Similarly, Figure 5 shows the changing trend of the queue length with the weight $V$ increasing. The length of system packet queue increases with the increase of weight $V$. As the weight $V$ increases, the impact of packet queuing on system performance is relatively reduced. Therefore, while the energy consumption of the system is reduced, the queue length of the whole packet is increased, which shows that the system can balance the system performance adaptively and optimize the whole system.

Under the condition that the weight of the EQPS is set to 2, the comparison results between the EQPS and the two baseline models are shown in Figures 6 and 7. Figure 6 shows the energy consumption comparison of the system, and Figure 7 shows the comparison of the packet queue length. The simulation results show that the long-term system energy consumption and long-term packet queue length of EQPS are the lowest, because EQPS can adaptively coordinate the packet transmission duration from the vehicle speed state and packet queue length, so as to improve the system efficiency. However, the EAS strategy cannot optimize the packet transmission delay according to the vehicle speed and packet queue length. The QW only optimizes the system from the perspective of packet queue length, ignoring the impact of vehicle speed on packet transmission delay. Therefore, the system performance of these two strategies is lower than that of EQPS.

## 5. Conclusions

In this paper, we study the packet scheduling problem of self-powered RSUs through passing vehicles' relaying under the background of Internet of Vehicles. In order to minimize the energy consumption of packet transmission from all self-powered RSUs to passing vehicles and improve the packet transmission efficiency of the system. In this paper, a distributed packet scheduling optimization strategy for energy-delay trade-off in self-powered RSUs is proposed. The strategy makes packet scheduling decisions according to the queue length of self-powered RSUs and the speed of passing vehicles. Taking the minimization of system energy consumption as the optimization objective, the energy-delay trade-off model is transformed and solved by using the Lyapunov optimization theory and knapsack problem's optimization algorithm with the main constraint of packet queue length of self-powered RSUs. According to the optimal solution of the above optimization algorithm, the optimal packet scheduling strategy is obtained. Simulation results show that the packet scheduling strategy proposed in this paper can effectively reduce the energy consumption and improve the packet transmission efficiency of the whole self-powered RSU system under the packet queue length constraint.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare no conflict of interest.

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