Int. J. Nonlinear Anal. Appl. 15 (2024) 1, 277–290
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.29258.4102

Optimization of energy consumption in smart city using reinforcement learning algorithm

Mohammad Ordouei[a], Ali Broumandnia[a,*], Touraj Banirostam[b], Alireza Gilani[c]

[a]Department of Computer, South Tehran Branch, Islamic Azad University, Tehran Iran

[b]Department of Technical and Engineering, Central Tehran Branch, Islamic Azad University, Tehran Iran

[c]Department of Mathematics, South Tehran Branch, Islamic Azad University, Tehran, Iran

(Communicated by Seyyed Mohammad Reza Hashemi)

Abstract

One of the most important challenges facing the evolution of smart cities over the last decade has been the optimization of energy use. Also, artificial intelligence and its algorithms, such as reinforcement learning, have appeared as a catalyst in the process of designing and optimizing smart services in the urban space, and in this issue, the generation and use of energy are critical factors. Using a technique based on reinforcement learning, the authors of this research successfully decreased and optimised smart city energy use. The suggested reinforcement learning method uses a collection of agents to cooperate together to achieve a shared objective using an optimum energy distribution policy (value action function). Agents' ability to cooperate to optimise energy use and save expenses is only one example of the many advantages that will accrue from their concerted efforts. To determine the worth of each option, the suggested technique looks at energy consumption data and the degree to which the option has been implemented in the past. This architecture ensures the device achieves an optimal balance between its energy footprint and the dependability of its communications. The simulation findings reveal that the yearly energy consumption in the smart city may be reduced by more than 35%-40% via the optimization of energy consumption using the proposed reinforcement learning approach.

Keywords: Reinforcement learning, Energy Optimization, Smart city
2020 MSC: 68T05, 80M50

1 Introduction

Considering the crisis caused by the consumption of fossil fuels in cities and the phenomenon of global warming, it is necessary to optimize energy consumption. during the past years, due to the advancement of technology, the smartness of cities and the way of life have changed a lot, and the subject of smart cities is Was considered in public. A smart city1 is an integrated environment of various components and smart items that improve the performance of structures by creating a logical connection compatible with the buildings and components of the city.

*Corresponding author
Email addresses: ordooei.mohammad@gmail.com (Mohammad Ordouei), broumandnia@gmail.com (Ali Broumandnia), banirostam@iauctb.ac.ir (Touraj Banirostam), a_gilani@azad.ac.ir (Alireza Gilani)

Received: April 2022 *Accepted:* July 2022

According to the definition of Liu et al. [18], the smart city refers to a place and region where natural resources are properly planned and create an ecosystem through various technologies and by providing integrated and smarter systems that can be used from resources. The basic aspect of a smart city is to create an information management system through the creation of an inclusive and coherent environment for cooperation and interaction between people, departments, and organizations to perform essential tasks such as business and daily affairs of citizens, and reducing energy consumption in these activities is one of the most basic goals of a smart city. Aside from the technologies used by a smart city, data analysts are also needed to evaluate the information provided by smart city systems [24]. Optimizing energy consumption in the smart city should be given more attention because, with the increase in network life, service quality and information transmission will be more efficient.

This article explains how reinforcement learning can be used to find the best energy-saving policy. The nodes are first clustered, and then the learning method, the Q-learning algorithm, is used to discover the optimization action. Based on the action-value function, this algorithm determines the proper action based on being in a specified state and doing a specific action in that state. This algorithm's purpose is to maximise the Q value function (to achieve energy consumption optimization).

The first part discusses the topic of energy and optimising energy use, as well as the significance of optimization and other concerns. In the second section, the core principles are discussed first, followed by an explanation of the research's background. The suggested approach is described in the third part, and the findings and assessments are presented in the fourth section. The conclusion is also addressed in the fifth part.

2 Related works

2.1 Basic concepts

The smart city is a new concept that many researchers consider as a solution to achieve the highest productivity and optimize resources against the problems of rapid urbanization and population growth [33, 19]. An essential issue in the Internet of things networks is data transmission for communication and human-to-human or human-machine interaction, since time and energy play a vital role in data transmission, it must be done in the shortest way [23]. A smart city includes smart energy, smart buildings, smart network, smart communication, and environmental awareness. The necessary approach in this city is to use advanced technology and informatics in order to improve the service level. Smart cities go through four actions to enhance the quality of life and the potential for economic development through a network of devices linked to the Internet and other technologies like data mining for analyzing data in different fields that would help for improving performance like prediction energy consumption and diagnosis of diseases [25].

These are the actions to take:

1. **Collection:** Data is gathered in real time via smart sensors.
2. **Analytics:** City services and operations are evaluated based on collected data.
3. **Communication:** The findings of data analysis are communicated to those in charge of making decision.
4. **Proceeding:** Actions are being done to enhance municipal operations, better manage assets, and improve the standard of living for city people [2].

To accomplish optimal energy management in a complex system, like a smart city, it is necessary to start with the most fundamental energy sources [30].

The implicit reliance between the various forms of energy must be specified [28], and it is necessary to identify and analyse the vast majority of them. Also, complete modeling is needed to validate the current advanced and modern systems [11]. Today, due to the increasing importance of security issues in the field of energy, we are more forced to store, intelligent energy management and use renewable energy sources [20]. Effective energy management in a smart building requires a concerted, on-going effort to enhance the facility's already high degree of energy efficiency [9]. In the proposed research about the smart city, several things should be prioritized, analysis and review of the capacities, existing obstacles, and basic criteria to achieve the smart city and check the degree of compliance of the buildings with the concept of a smart city. In addition to laying the foundation for optimizing energy consumption and its management, the gradual improvement of the technology level of the main building elements of a city (buildings) to achieve a smart city [37].In the study conducted by Calvillo and his colleagues [8], all fields related to energy in the smart city and all its connections were investigated, Various existing models and simulation tools are presented. The smart city is a stable and efficient urban center that delivers a high quality of life for its citizens with effective management of its resources. Because of the complexity and importance of energy systems, energy management is a topic of discussion in densely populated areas. Therefore, a lot of time and effort has to be spent fixing this issue. Typically, modelling and simulation are the go-to methods for gauging the potential outcomes of smart solutions in terms of technology and policy, and for laying out the most efficient paths for existing cities to evolve into smarter ones [27].

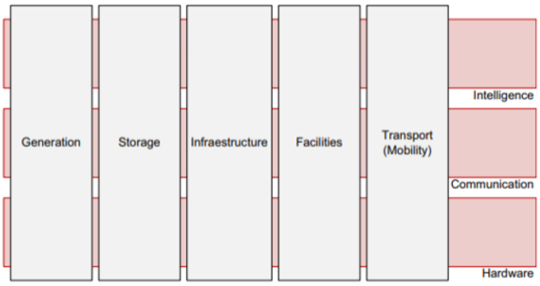

Figure 1: Segmenting Smart City Energy Intervention Zones.

The findings of this research in [34] demonstrate that in the future of smart cities, the primary focus will be on energy-efficient facilities with improved applications, control systems, and demand-based designs. In another study conducted by Petritoli. [21], the basic energy consumption of the lighting system is compared with a predefined simulated system. In this way, the lighting system can be adjusted based on the existing traffic rate, which is averaged according to the days of the week [8]. Azizivahed and his colleagues [5] have investigated the reduction of energy consumption and its optimization with the help of the combination of energy consumption simulation software in the city, and advanced machine learning algorithm creation software. The use of this method makes it possible to measure the learning control algorithms and their capacity and ability in different cities and to provide a platform for smart energy management.

The smart city and especially the smart energy has supervision and control, and in general energy management is more specifically provided to the officials and consumers [16]. When the indicators of the comfort of the residents' lives and their real needs are unmistakably established using sophisticated and cutting-edge techniques, certainly the management of energy production and provision can also be done according to the accurate measurement of these needs.[31]. This not only helps save money on utility bills, but it also paves the way for the eventual realisation of a ”smart city” and the full automation of all structures [3].

Smart production and consumption management were initially proposed by Glavi and his team [12]. Based on their findings, smart production and consumption management in a power system that takes in electricity and gas as input and can choose the quantity and timing of purchasing and selling energy to the upstream network is possible. In the administration of energy storage, many energy carriers may be employed or converted to each other. By optimising the administration of the smart grid, it is possible to choose the most appropriate energy supply system for every given load [18]. A power management strategy and an energy management strategy are required to make effective use of a network that includes more than two dispersed production units, especially in the case of being disconnected from the network. This program aims to minimise total costs by reducing the present value of energy infrastructure. There are two general policies for the presence of the intelligent energy production management network in the market environment. First, the entire demand of the intelligent energy production management network is provided by local sources, without taking into account the exchange with the upstream network. Based on this, the operator of the intelligent energy production network must minimize the operating costs of the intelligent energy production management network every hour. Second, the operator of the intelligent energy production management network has the ability to exchange power at the market price with the upstream network and based on this, the operator seeks to minimize operating costs and maximize the amount of production for sale to the upstream network, and as a result, optimize It is own income [22]. Energy production management programs in a smart city are divided into two general categories:

1. An incentive-based approach is taken to energy production management in a smart city within the framework of the Internet of Things, with the goal of encouraging residents to save power during peak demand.
2. The management of energy production in a smart city is based on price, in this response variable tariffs with time are used according to the costs related to electricity production: Consumers can reduce their electricity bill by not using in hours with high prices or by changing consumption in times with low price [38]. Energy production management programs in a smart city in the context of the Internet of Things are divided into two general categories:

The first category of programs in which the consumption resources cut the load according to the instructions or the signal they receive from the system operator, which are called controllable energy production management programs.

The second category of programs in which the consumption resources cut the load according to the price and do not receive instruction or a signal from the system operator to cut the load, which are called uncontrollable load response programs.

Energy production management programs in a smart city consist of three categories:

The first category is the programs that are based on reliability and are mostly used in emergency situations.

The second category is programs that are based on economics and consumption resources which are planned based on the proposed price and market conditions.

The third category is the ancillary service programs, which are classified into two categories: reservation and regulations [13].

2.2 Research background

Energy optimization for EVs in a smart city was the topic of some papers [36]. There has been a tremendous rise in the popularity of electric cars (EVs) as a significant eco-friendly project that, if properly integrated into the urban environment, may serve as a symbol of the host city's dedication to sustainable transportation and an integral part of the smart city idea. Optimal energy efficiency in electric cars and their connectivity to a smart city are topics investigated in this article. In sum, the core principle supporting the current investigation may help policymakers, automakers, and transport providers better understand and use EV technologies within the context of smart cities. In order to communicate particular information on the state of cars and road conditions, the suggested method is based on communication between vehicles and buildings.

The basic idea behind this technique may be broken down into two sections. The first is concerned with car categories, while the second is with building types. Using a support vector classification approach, we are able to resolve the classification issue. AI is used to handle the problem of making recommendations, with a neural network being used to get the optimal conclusion. An old car's data may be used to determine the best course of action inside the building, and this information can then be transmitted to a new car so that it can maximise its efficiency in terms of energy use within the same structure. Multiple approaches and scenarios were covered in this method. Matlab's Simulink was used to verify the effectiveness of the suggested approach to power management. To demonstrate the efficacy of this approach, we compared the charging outcomes and energy usage at the conclusion of this study.

As one step toward creating smart cities, [16] proposed a machine learning-based method for managing public sector energy efficiency in 2021. Buildings are the single greatest user of energy in the United States; this is particularly true of heavily used public buildings like schools, hospitals, government offices, and other community hubs. As public sector energy efficiency is a key component of the smart city idea, this article seeks to solve the issue of how to integrate a Big Data platform and machine learning into an intelligent system to manage such efficiency. Predictive models for energy usage in Croatian government buildings were developed using deep neural networks, regression trees, and random forests, all of which made use of variable reduction techniques. This study also covers the technical prerequisites for developing such a platform that can be utilised by public management to plan rehabilitation measures for public buildings, save energy consumption and costs, and link such smart public buildings as part of smart cities. An improvement in government energy management efficiency, a rise in service quality, and a safer and cleaner environment are all possible thanks to this digital change in contemporary energy management.

Zekić-Sušac et al. [35] report focused on smart lighting as the smart city's foundational technology. The research team in Rome wanted to model the energy savings from the smart street pilot system and compare it to actual consumption data. We simulate a regulation and compare its effect on the astronomical lighting system's baseline power usage to the regulation's actual effect. The baseline consumption is compared by modelling an adaptive configuration based on the traffic flow rate, and the lights are dimmed based on statistical averages of the traffic flow rate, which are broken down by day of the week and the brightness level.

Towards the end of 2018, Petritoli et al. [26] introduced a flexible modelling framework for smart city energy management systems. Energy supply and consumption have taken centre stage as the world grapples with the effects of global warming. In this study, we show how to create a model of a smart city complete with a distribution network (DN) by combining data from a variety of sources into a unified modelling framework for cooperative energy management systems (EMS). Models of several EMSs are included in this framework to mimic power flow, electrical losses, and voltage in DN in order to monitor power system operation or manage consumer-installed devices. Findings demonstrated the framework's adaptability and its applicability to a wide range of smart city problems.

In 2019, Hayashi et al. [15] employed IoT-based smart edge computing for energy management in smart cities. With the explosion of interest in "smart cities," green energy management systems (smart grid, smart buildings, etc.) have attracted a lot of attention in academia and business. In this work, we use edge computing, deep reinforcement learning, and the Internet of Things to create an energy management system. First, energy management based on the Internet of Things in smart cities is explained. Next, a framework and software model for an IoT-powered, edge-computing system are provided. Then, we provide the suggested framework with a deep reinforcement learning-based scheduling approach that minimises energy consumption.

To integrate the Green Internet of Things in smart cities, Liu et al. [18] suggested an energy-balanced clustering protocol in 2020. Using the concept of the Internet of Things (IoT), this study establishes a green wireless sensor network (WSN) to enhance sensor-based communication in potential smart cities. It's crucial to take precautions against energy depletion and to advocate for energy-efficiency strategies if green IoT is to be implemented. However, the effectiveness of clustering relies on the quality of the clustering techniques used, which may significantly affect the lifespan of such networks. This research presents an enhanced adaptive ranking-based opportunistic routing protocol (I-AREOR) based on areal density, relative distance, and residual energy to strike a compromise between energy consumption and network longevity. The results demonstrate that the suggested clustering method outperforms the state-of-the-art techniques in optimising network longevity.

Chithaluru et al. [10] categorised energy efficiency strategies for smart cities in 2021. Low-consumption and optimization solutions for transportation, government, and inhabitants' quality of life in a smart city are essential in light of recent years' unprecedented urbanisation. Applications for smart cities may be found in the complex and widespread Internet of Energy (IoE) ecosystem. Increases in both the availability and popularity of Internet Energy devices and apps have led to a rise in demand for related software. Consequently, it is essential for smart city solutions to be energy efficient and adept at handling problems of this kind. Additionally, in the context of the Internet of Energy, energy optimization strategies may be used to cut down on power usage, therefore contributing to the achievement of sustainability targets. Researchers from all across the globe have presented their own methods for optimising energy use in various contexts. Optimization of energy use is also necessary in computing systems. As a result, there is a growing focus on the issue of energy usage in data center, cloud, and block chain (BC)-based systems. In this study, we explore energy optimization strategies for various systems, including BC-based approaches. We have provided a taxonomy for organising strategies for maximising energy efficiency. High Performance Proof Optimization is a consensus process that we've suggested for high-performance computing ecosystems that is both energy-efficient and fast. Then, we talk about the remaining questions and difficulties in energy optimization.

In order to provide smart cities with a reliable and environmentally friendly power, Tanwar et al. [32] proposed a hybrid smart grid. A smart city is a secure and productive metropolitan region that provides its citizens with high standards of living via optimum resource planning. Consumers now have more reliable and secure access to their homes' resources because of the proliferation of "smart cities." This makes power management a complex task that requires careful scheduling of linked devices to achieve maximum efficiency. This work presents a hybrid smart grid that optimises energy costs in real time (ECRT) by taking the coefficient of delay into account. The grid uses many energy sources, including solar (PV), hydroelectric (HyD), and thermal (Thermal) (FoL). In order to regulate power consumption more effectively, this study aims to develop smart grid (SG) resources for that purpose. This article simulates renewable energy derived from ecologically sound resources and sets up an efficient energy distribution network for a smart city. The concepts and smart energy solutions presented in this article advance the state of the art in a number of fields that study how to maximise productivity, efficiency, and longevity in their construction.

For smart cities, Tanwar et al. [32] proposed a hybrid smart grid powered by environmentally friendly energy sources. A smart city is one that maximises its use of resources to ensure the safety and prosperity of its citizens. With the rise of "smart cities," homeowners may confidently and easily manage their homes' systems. This makes power management a complex task that requires careful planning on when to use which linked devices. Taking into account the coefficient of delay, this study presents a hybrid smart grid that can produce power from photovoltaic (PV), hydroelectric, and thermal sources using a single system, all while optimising energy costs in real time (ECRT) (FoL). The study's focus is on a smart grid (SG) in order to develop means of controlling power use more effectively. In order to maximise energy efficiency in a smart city, this article simulates renewable power derived from ecologically sound sources and sets up a functional and well-coordinated energy distribution network. This article covers a range of concepts and smart energy solutions that advance the state of the art in a number of fields concerned with optimising performance, making smart and efficient use of resources, and designing for sustainability.

During the same time period, Alazab et al. [1] introduced a dynamic integrated IoT system for green energy in smart cities. A growing number of cities around the world are focusing their infrastructure strategies on sustainable mobility policies, modern energy storage, increased renewable energy production, enhanced waste management, and the introduction of ICT infrastructure in response to fundamental social and environmental changes at the global level. Smart city energy systems need a substantial contribution from both heat and power resources, as well as a high degree of connectivity between homes and businesses in the city's infrastructure. In this study, we present an Internet of Things architecture for smart cities that is built on smart green energy (IoT-SGE). Through omnipresent monitoring and encrypted communications, the Internet of Things allows smart cities to regulate their energy use. In this research, we explore how deep reinforcement learning might inform the development of an IoT-based intelligent energy management system. The study's findings demonstrate the value of the Internet of Things (IoT) sensors in monitoring energy usage, forecasting energy needs in smart cities, and reducing associated costs. Table 1 summarizes the research works in related to the optimization of energy consumption in smart city using different algorithms.

Table 1: An overview of the related methods

Reference	**suggested method**	**Findings**
[5]	In order to classify data, a support vector machine is used. In order to tackle the problem of making a suggestion, they turned to AI principles, and a neural network was employed to make the most optimal choice.	By contrasting the battery charge status with the total amount of energy used, the effectiveness of this procedure was shown.
[4]	To generate energy consumption prediction models for public sector buildings in Croatia, deep neural networks, regression tree, and random forest with variable reduction approaches were employed.	Such digital revolution in energy management may improve government management's energy efficiency, service quality, and environmental safety.
[35]	The goal of this project was to simulate and evaluate energy savings based on data from the Smart Street prototype system in Rome.	Based on statistical averages of traffic flow rates, varied by day and week, the lights may be lowered (thereby lowering consumption), and the baseline consumption is compared to the simulation of an adaptive design based on traffic flow rates.
[26]	This study describes the development of a Cooperative Energy Management Systems (EMS) modeling framework that develops a virtual model of a smart city with a distribution network (DN) based on a broad range of real-world data.	The findings demonstrated that the framework is very adaptable and can be used to a wide range of smart city challenges.
[15]	We are concentrating on the development of an Internet of Things-based energy management system based on an edge computing infrastructure and deep reinforcement learning.	For the suggested framework, an energy-efficient deep reinforcement learning scheduling strategy is given.
[18]	Based on regional density, relative distance, and residual energy, this study presents an improved adaptive ranking-based opportunistic routing protocol (I-AREOR).	The findings reveal that the suggested clustering approach outperforms the current techniques in terms of maximizing network lifespan.
[10]	A taxonomy of energy optimization approaches was presented. High Performance Proof Optimization, an energy-efficient consensus technique for high-performance computing-based ecosystems, is also proposed in this paper.	Energy optimization issues and open problems are highlighted.
[32]	It provides a hybrid smart grid that produces power from various photovoltaic (PV), hydroelectric, and thermal sources, as well as a delivery system that performs energy cost optimization in real time (ECRT) while accounting for delay (FoL).	It provides diverse concepts and smart energy solutions that advance multiple disciplines focused on enhancing performance, smart and efficient resource usage, and sustainable design.

[17]	uses a modified ridership optimization method to provide an innovative technique to cluster vertex selection (ROA).	The suggested method's performance is validated by a comparative examination of multiple advanced optimization models in terms of the number of live nodes and normalized energy.
[1]	For smart cities, a Smart Green Energy-based Internet of Things (IoT-SGE) is suggested. Smart cities may regulate energy via pervasive monitoring and secure communications by utilizing IoT. This work focuses on the creation of an intelligent energy management system enabled by deep reinforcement learning that is based on the Internet of Things.	The findings suggest that IoT sensors may be used to monitor energy usage, estimate energy demand in smart cities, and save money.
[18]	Based on regional density, relative distance, and residual energy, this study presents an improved adaptive ranking-based opportunistic routing protocol (I-AREOR).	The findings reveal that the suggested clustering approach outperforms the current techniques in terms of maximizing network lifespan.
[10]	A taxonomy of energy optimization approaches was presented. High Performance Proof Optimization, an energy-efficient consensus technique for high-performance computing-based ecosystems, is also proposed in this paper.	Energy optimization issues and open problems are highlighted.
[32]	It provides a hybrid smart grid that produces power from various photovoltaic (PV), hydroelectric, and thermal sources, as well as a delivery system that performs energy cost optimization in real time (ECRT) while accounting for delay (FoL).	It provides diverse concepts and smart energy solutions that advance multiple disciplines focused on enhancing performance, smart and efficient resource usage, and sustainable design.
[17]	uses a modified ridership optimization method to provide an innovative technique to cluster vertex selection (ROA).	The suggested method's performance is validated by a comparative examination of multiple advanced optimization models in terms of the number of live nodes and normalized energy.
[1]	For smart cities, a Smart Green Energy-based Internet of Things (IoT-SGE) is suggested. Smart cities may regulate energy via pervasive monitoring and secure communications by utilizing IoT. This work focuses on the creation of an intelligent energy management system enabled by deep reinforcement learning that is based on the Internet of Things.	The findings suggest that IoT sensors may be used to monitor energy usage, estimate energy demand in smart cities, and save money.

3 proposed method

One of the ways to make control systems smarter to reduce energy is through reinforcement learning-based algorithms. This learning, inspired by human intelligence and behavior, teaches the ability to learn systems. In this article, using the Q-learning algorithm as one of the reinforcement learning methods, it is necessary to increase the speed of learning. In order to better distribute the load transfer, in the first step, by using the maximum reward for Q-learning and also using the condition for updating the value function, which is inspired by the Q-learning method, improves the convergence speed. It is used to increase network life and reduce energy consumption.

In order to optimise energy in the smart city, we need a coordinating agent that forms a cluster based on a specific criterion: the locations of the agents. After forming the clusters, the first member of each cluster is considered the head, and the rest of the members are considered members. The message sending unit will send messages related to cluster heads and sub-members. All agents of a group will, at the end of each iteration, send their tables to the Q-learning learning agent as follows. The cluster head is selected dynamically according to its energy. The base station announces the cluster head and calculates the residual energy. In this article, by providing a suitable communication framework between agents, a new method for energy optimization using the q algorithm is presented through communication between agents. In reinforcement learning, the environment is a collection of S possible states such that at any moment the agent can perform one of A possible actions. The agent may receive a reward for the action or set of actions he performs. This reward may be positive or negative. The agent moves in the environment and remembers the corresponding states and rewards and behaves in such a way that he does not consider the reward function to be the maximum. The total reward is the sum of the rewards that the agent has collected over time. An agent is an artificial intelligence that is a learner. An agent chooses an action and applies it to the environment [6].

A- Determining the goal: The purpose of the agent is determined in the section determining the purpose. Then the agent waits to receive the message, and after receiving the message, the cluster head and sub-members are separated from each other. Sub-members are waiting for the group leader to make the necessary decisions.

B- Determining the situation: The head of the cluster chooses the situation for himself and his cluster in relation to the final destination and the members of the group with other sub-members of the group and informs the sub-members of the group as well. This work is carried out by the status determination unit.

C- Determining the mode: In the status determination unit, the head of the cluster tells the other people in the group where they stand in terms of their final destination and current goal.

D- Select action: By referring to the Q table related to his state, the agent of the group selects the pair (state, action) that has the same state as their state and has received the highest reward. Now the agent can choose the action recommended by the suitable pair selection unit with a certain probability or choose other modes. The state and actions of all the agents in the group as well as the current target location are kept in the memory of the head agent so that in the next iteration, according to the changes in the environment, the reward is allocated [7]. It should be noted that the task of the agent is to establish coordination between the groups, and the task of the group leader is to establish cooperation between the members of a group. One of the ways to establish proper coordination is to use the language of agents' communication [29]. Agents are able to monitor and communicate numerous environmental characteristics. The deployment of agents is the first stage in developing an algorithm for reinforcement learning. Then, it determines the needed energy for data transport. As Eth, we control this energy. If a node's energy level is more than or equal to Eth in each round, the agent will transfer data. If a node's energy level falls below Eth, it cannot send data. When the energy level falls below the ETH value, the device will enter sleep mode to save power. Before executing the software, the following procedures are taken to determine the surface energy of each node based on their distance.

- Case 1: Er > Eth: When Er exceeds Eth,

  The node is operational and prepared for communication.

- Case 2: Er < Eth: when Er is smaller than Et,

  The node transitions to a state where it stores energy.

We use the following formula to calculate Eth. relationship (1-3)

$$E_{th} = ((E_{TX} + E_{DA}) * D) + (E_{amp} * D * d_4) \tag{1}$$

where D represents the length of the data packet and d represents the maximum distance between the node and the sink. It is based on the data of the transmission mechanism for CH reception and forwarding $(D_1 + D_2 + D_3 + ... + D_N) and (D_{CH} + D_1 + D_2 + D_3 + ... + D_N)$.

If CH is inside the distance range N, $d < d_0$, data transfer from N to CH will use energy.

$$E_N^{CH} = D_N^{CH}(E_{ele}) + D_N^{CH}(E_{fs})(d^2) \tag{2}$$

Relationship 3-2: According to the network paradigm, nodes participating to the CH transmit both their own data and the data created by member nodes. Nodes that are not CH are exempt from sending data. Assume that the nodes are deployed at random and that there is no requirement to aggregate data at any of the sent nodes. based on the mechanism for receiving and transmitting data CH is $(D_1 + D_2 + D_3 + ... + D_N)$, $(D_{CH} + D_1 + D_2 + D_3 + ... + D_N)$ If the distance between N and CH is $d < d0$, energy is required to transmit data from N to CH.

Now considering the circumstance when the distance between N and CH is $d > d_0$.

Relationship 3-3:

$$E_N^{CH} = D_N^{CH}(E_{ele}) + D_N^{CH}(E_{amp})(d^4) \tag{3}$$

The amount of power required by CH to transfer data to S at a distance of $d < d_0$:

Relationship 3-4:

$$E_{CH}^{S} = D_{CH}^{S}(E_{ele}) + E_{DA} + D_{CH}^{S}(E_{fs})(d_2) \tag{4}$$

Relationship 3-5:

$$E_{Total-CH} = E_{CH} + E_N \tag{5}$$

Relationship 3-6:

$$E_{Average-CH} = \frac{E_{Total-CH}}{N} \tag{6}$$

Relationship 3-7:

$$E_{Save-N} = E_{elec} + E_{TX} + E_{amp} \tag{7}$$

Relationship 3-8:

$$E_{Save-CH} = E_{ele} + E_{DA} + E_{TX} + E_{RX} + E_{amp} \tag{8}$$

Relationship 9-3:

$$E_{Save-Total} = \sum_{i=0}^{n} E_i \tag{9}$$

The suggested method's flowchart is shown in Figure 2.

4 Evaluation of results

The proposed method is implemented using the MATLAB programming language. In the simulation, we consider a network with n (states and actions) randomly deployed in a square field. A scenario is considered in which agents are deployed randomly. In a given area, some are in storage mode to conserve energy, cover, and connect. Energy is unlimited in the proposed model.

The Q learning plan consists of four major phases: (1) the initial phase, (2) the threshold calculation phase, (3) the group formation phase, and (4) the energy optimization phase. The system then determines the needed energy for data transfer. If the energy level of a node in each group is more than or equal to Eth, the group will transfer data to its members. If a node's energy level drops below Eth, it cannot communicate data between members. When the energy level falls below the Eth value, the mode changes to storage to save energy. Cluster heads need more energy to transmit. Based on the Q schedule, agents pick actions and apply them to the environment. Reinforcement learning is a technique in which the agent picks one of all potential actions based on the state of the environment, and in exchange for completing that action, the environment sends a numerical signal called reward. The agent's objective is to discover, via trial and error, a policy whose implementation will provide the greatest potential reward. Table 2 shows the simulation settings utilised in MATLAB.

A wireless sensor network is used in the smart city, which includes sensor nodes. Each sensor node consumes energy, the proposed method seeks to optimize the nodes' energy consumption by using clustering and choosing the cluster head first and then by using reinforcement learning algorithm. Although the selection of the cluster head is done randomly, the reinforcement algorithm plays a significant role in it. Figure 3 shows the output of the cluster header selection section. The blue ones are normal nodes and the red ones are cluster heads.

Once started, the cluster head is responsible for receiving information from its own cluster. At the beginning of the work, before the environment is searched, Q obtains the desired constant values, but with the start of the agent search in the environment, Q reduces the energy consumption better and better for the cluster head determination

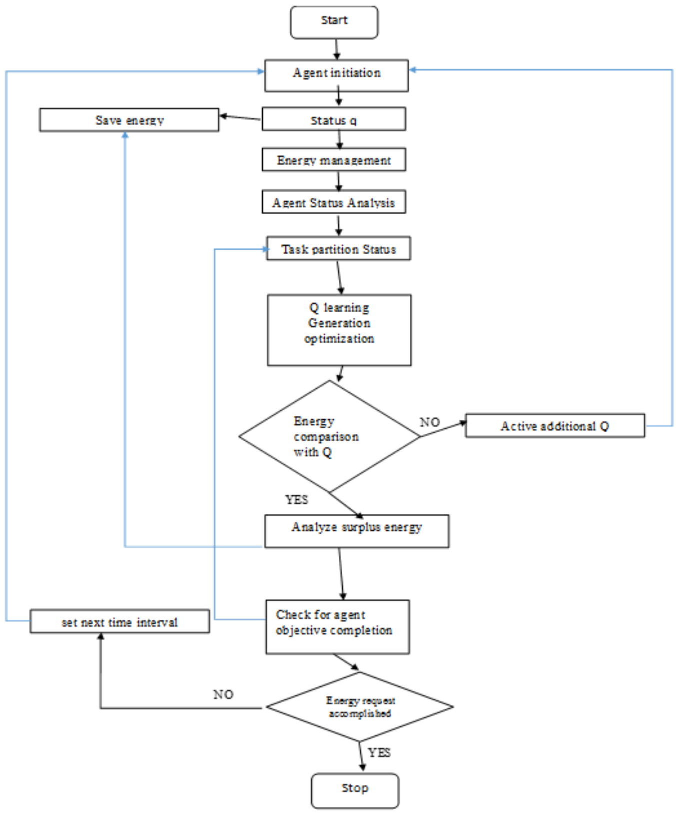

Figure 2: Diagram illustrating the suggested procedure

Table 2: Network parameters

N	Total number of nodes: 100 Dimensions: 1000×1000
E_0	Sum total of a node's energy: 0.5 j
P	Probability of cluster head: 0.1
E_{RX}	Energy dissipation: receiving $0.0013/pj/bit/m4$
E_{fs}	Energy dissipation: free space model $10/pj/bit/m2$
E_{amp}	Energy dissipation: power amplifier $100/pj/bit/m2$
E_{ele}	Energy dissipation: electronics 50nj/bit
E_{TX}	Energy dissipation: transmission $50/nj/bit$
E_{DA}	Energy dissipation: aggregation $50/nj/bit$
d_0	Reference distance: 67 meter
N	Number of sleep nodes: 20Nodes
E_r	

section until the start of the node and sending to the environment. gives and all the primary energy is no longer used. Results are shown in Figure 4.

In Figure 4, cluster heads control their nodes through Q learning. As long as it retains energy, the cluster head will continue to serve as the leader of the cluster, and the reinforcement process will be used to randomly choose a new leader. Each cluster's leader is responsible for establishing links amongst the various subclusters. The first graph of energy use is shown in Figure 5.

You can see that the use of reinforcement algorithms will increase the speed of reinforcement learning and will also bring better results. Finally, the output of the deployment and the cluster heads will be Figure 6, which of course has slight changes compared to Figure 6.

When we compare the network in Figure 3 at the time of random deployment and selection of cluster heads with the network in Figure 6 during routing, we can see that there have been only minor changes made to the network and

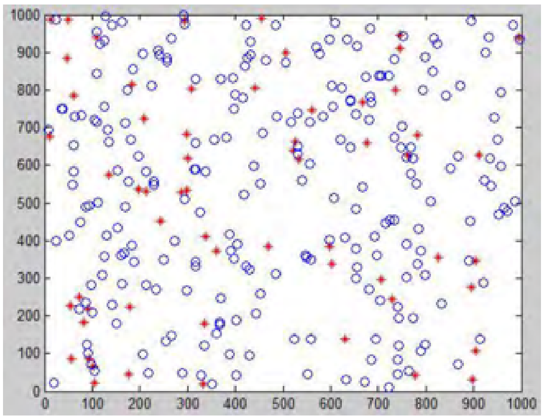

Figure 3: Selection of cluster heads

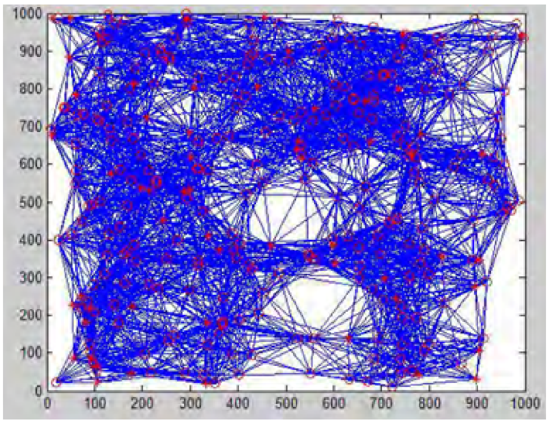

Figure 4: The routing of data between clusters, facilitated by the cluster leader, and the linking of individual clusters.

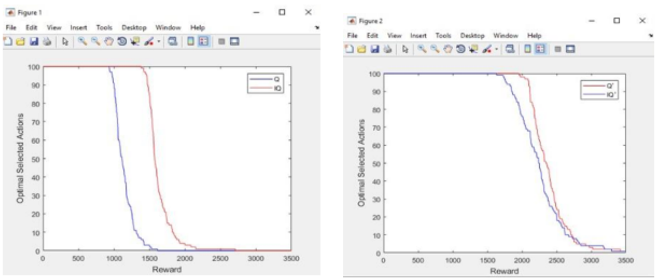

Figure 5: Energy consumption reduction chart (A and B)

that energy consumption has decreased for both the clusters and the entire network.

5 Conclusion

We presented a framework for collaborative learning of agents in dynamic environments in this article. Given that we are frequently faced with a large state space in multi-agent environments, and that the environment is dynamic and uncertain, agent learning will be a difficult issue. For this task, a reinforcement learning method was presented. Using a reinforcement algorithm solution based on Q-Learning can help to improve energy efficiency. One of the issues raised by smart cities is the lifetime and energy of nodes. As a result, much research has been conducted in this field, primarily using learning algorithms or combining algorithms. Because a large number of IoT (internet of things) applications generate a large amount of data for processing, the most important benefit of reinforcement learning in the case of Q-Learning is improved performance with large data scales. Another advantage of reinforcement learning

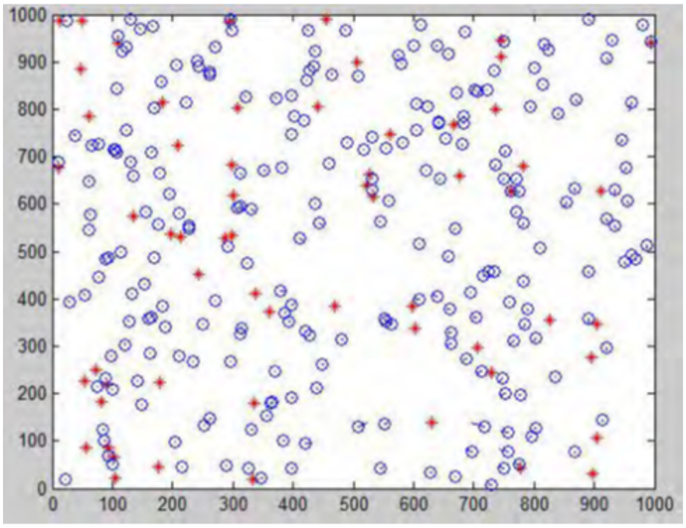

Figure 6: The final position after applying reinforcement learning with minimum energy consumption.

is that it can automatically extract new features for various problems. When nodes are not involved in transmission, energy is constantly generated, and this excess energy can be transferred to the mobile charger and load "energy," which is a high energy source in and of itself. As a result, energy flows in both directions between the mobile charger and the node. Because energy can be collected or transmitted from nodes at different points, two-way energy flows encourage planning to reduce high energy consumption. The distance between nodes in energy interactions causes this limitation. The energy status of the nodes is updated after the energy flow is sent. It is obvious that the flow of data is strongly related to the flow of energy, which will result in lower energy consumption. The smart city faces three major challenges: energy consumption, network coverage, and security. The smart city contains a large number of sensors, the purpose of which is to collect and process information from the environment in opposition to the node or agent. To achieve long-term and stable operation for nodes, energy transfer technology is proposed. As a result, the nodes transfer energy as well as data. As a result, in IoT energy saving, energy flow is accompanied by data flow. Furthermore, if the Internet of Things system requires more transmissions, increasing the number of retransmissions and rejecting processes will result in higher energy consumption. Many changes and benefits have resulted from the introduction of the Internet of Things in the field of energy. At both the urban and industrial levels, new technologies have made significant contributions to the production, transmission, and better use of energy. In addition, smart cities help communities provide the energy they require at a much lower cost by utilising recycling and cost-cutting methods. The equipment used to generate energy can be monitored using IoT. This technology protects the overall equipment, improves its performance, and simplifies maintenance. It is extremely difficult, for example, to find any problems or defects in complex equipment such as turbines. An intelligent model based on multi-factor systems for energy management in smart cities is presented for this purpose, and it has been successfully converted into energy production systems. Multi-agent systems are made up of several intelligent and diverse agents that work together to achieve the system's goal. The network's dynamic process selects the cluster's head at random and expands it to the maximum value using reinforcement learning. The obtained results show that the network's energy consumption has decreased. The algorithm of each agent has distributed the amount of electric energy production among the consumers based on the existing demand in the smart city, and the problems of production development planning and transmission development planning will be integrated and presented as a hybrid model.

In this research, the following were shown:

- The proposed method can prevent the increase in energy consumption based on the Internet of Things.
- The proposed method can guarantee the energy consumption, integrity, and accuracy of the data in the connection between the IOT components.
- The proposed method can lead to a reduction of computational complexity, memory costs, and communication overhead that is related to energy consumption compared to the existing methods.

References

[1] M. Alazab, K. Lakshmanna, Q.V. Pham and P.K. Reddy Maddikunta, *Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities*, Sustain. Energy Technol. Assess. **43** (2021), 100973.

[2] V. Albino and U. Berardi, *Dangelico RM (2015) Smart cities: definitions, dimensions, performance, and initiatives*, J. Urban Technol. **22** (2015), 1–19.

[3] G. Amelie, M. Serrano and Gh.A. Atemezing, *Semantic web methodologies, best practices and ontology engineering applied to Internet of Things*, IEEE 2nd World Forum on Internet of Things (WF-IoT), 2015, pp. 412–417.

[4] F. Aymen and C. Mahmoudi, *A novel energy optimization approach for electrical vehicles in a smart city*, Energies. 12(5) (2019).

[5] A. Azizivahed, A. Arefi, S. Ghavidel, M. Shafie-khah, L. Li, J. Zhang, and J.P.S. Catalão, *Energy management strategy in dynamic distribution network reconfiguration considering renewable energy resources and storage*, IEEE Trans. Sustain. Energy **11** (2020), no. 2, 662–673.

[6] T. Banirostam and M.N. Fesharaki, *A new approach for biological complex adaptive system modeling and simulation*, Life Sci. J. **9** (2012), no. 3, 2257–2263.

[7] T. Banirostam and M.N. Fesharaki, *Effective parameters in convergence of autonomous distributed systems using with immune system approach*, 10th Int. Symp. Autonomous Decentr. Syst. (ISADS-IEEE), 2011, pp. 204–208.

[8] C.F. Calvillo, A. Sánchez-Miralles and J. Villar, *Energy management and planning in smart cities*, Renew. Sustain. Energy Rev. **55** (2016), 273–280.

[9] H. Carlos, E. Biele, Ch. Martini, M. Salvio and C. Toro, *Impact of energy monitoring and management systems on the implementation and planning of energy performance improved actions: An empirical analysis based on energy audits in Italy*, Energies **14** (2021), no. 16, 4723.

[10] P. Chithaluru, F. Al-Turjman, M. Kumar and T. Stephan, *I-AREOR: An energy-balanced clustering protocol for implementing green IoT in smart cities*, Sustain. Cities Soc. **61** (2020), 102254.

[11] G. Gianfranco, M. Lupia, G. Cario, F. Tedesco, F. Cicchello Gaccio, F. Lo Scudo and A. Casavola, *Advanced adaptive street lighting systems for smart cities*, Smart Cities **3** (2020), no. 4, 1495–1512.

[12] M. Glavic, *Agents and multi-agent systems: A short introduction for power engineers*, University of Liege - Electrical engineering and computer science department, 2006.

[13] Y. Guo, Q. Wu, H. Gao and F. Shen, *Distributed voltage regulation of smart distribution networks: Consensus-based information synchronization and distributed model predictive control scheme*, Int. J. Electric. Power Energy Syst. **111** (2019), 58–65.

[14] S.M.R. Hashemi, H. Hassanpour, E. Kozegar and T. Tan, *Cystoscopy image classification using deep convolutional neural networks*, Int. J. Nonlinear Anal. Appl. **10** (2019), no. 1, 193–215.

[15] Y. Hayashi, Y. Fujimoto, H. Ishii, Y. Takenobu, H. Kikusato and Sh. Yoshiza, *Versatile modeling platform for cooperative energy management systems in smart cities*, Proc. IEEE **106** (2018), no. 4, 594–612.

[16] A. Kari and S. Sierla, *An overview of machine learning applications for smart buildings*, Sustain. Cities Soc. **76** (2022), 103445.

[17] M.I. Khalil, N.Z. Jhanjhi, M. Humayun, S. Sivanesan, M. Masud and M.S. Hossain, *Hybrid smart grid with sustainable energy efficient resources for smart cities*, Sustain. Energy Technol. Assess. **46** (2021), 101211.

[18] Y. Liu, C. Yang, L. Jiang, S. Xie and Y. Zhang, *Intelligent edge computing for IoT-based energy management in smart cities*, IEEE Networks **33** (2019), no. 2, 111–117.

[19] Z. Magubane, P. Tarwireyi and M.O. Adigun, *Evaluating the energy efficiency of IoT routing protocols*, Proc. 2019 Int. Multidiscip. Inf. Technol. Engin. Conf.(IMITEC), Vanderbijlpark, South Africa, 21–22 November 2019; IEEE: Piscataway, NJ, USA, 2019, pp. 1–7.

[20] A. Mathiesen, B. Vad, H. Lund, D. Connolly, H. Wenzel, P. Alberg Qstergaard, B. Möller and S. Nielsen, I. Ridjan, P. Karnøe, K. Sperling and F.K. Hvelplund, *Smart Energy Systems for coherent 100% renewable energy*

and transport solutions, Appl. Energy **145** (2015), 139–154.

[21] S. McClellan, J.A. Jimenez and G. Koutitas, *Smart Cities: Applications, Technologies, Standards, and Driving Factors*, Springer International Publishing, 2017.

[22] E. Mlecnik, J. Parker, Z. Ma, C. Corchero, A. Knotzer and R. Pernetti, *Policy challenges for the development of energy flexibility services*, Energy Policy **137** (2020), 111147.

[23] P. Neamatollahi, M. Naghibzadeh and S. Abrishami, *Distributed clustering-task scheduling for wireless sensor networks using dynamic hyper round policy*, IEEE Trans. Mob. Comput. **17** (2017), 334–347.

[24] M. Ordouei and T. BaniRostam, *Integrating data mining and knowledge management to improve customer relationship management in banking industry (Case study of Caspian credit institution)*, Int. J. Comput. Sci. Network **7** (2018), no. 3, 208–214.

[25] M. Ordouei and T. Banirostam, *Diagnosis of liver fibrosis using RBF neural network and artificial bee colony algorithm*, Int. J. Adv. Res. Comput. Commun. Engin. **11** (2022), no. 12, 45–50.

[26] E. Petritoli, F. Leccese, S. Pizzuti and F. Pieroni, *Smart lighting as basic building block of smart city: An energy performance comparative case study*, Measurement **136** (2019), 466–477.

[27] P. Pirozmand, A. Javadpour, H. Nazarian, P. Pinto, S.S. Mirkamali and F. Jafari, *GSAGA: A hybrid algorithm for task scheduling in cloud infrastructure*, J. Supercomput. **78** (2022), no. 15, 17423–17449.

[28] K. Pourjavan, *Explanation of smart city and smart transportation solutions*, Karafan **16** (2019), no. 1, 15–35.

[29] N.P. Rana, S. Luthra, S.K. Mangla, R. Islam, S. Roderick and Y.K. Dwivedi, *Barriers to the development of smart cities in Indian context*, Inf. Syst. Front. **21** (2019), 503–525.

[30] S. Rasaneh and T. Banirostam, *A new structure and routing algorithm for optimizing energy consumption in wireless sensor network for disaster management*, 4th Int. Conf. Intell. Syst. Model. Simul., 2013, pp. 481–485.

[31] M. Stonebraker, U. Çetintemel and S. Zdonik, *The 8 requirements of real-time stream processing*, ACM Sigmod Record. **34** (2005), no. 4, 42–47.

[32] S. Tanwar, A. Popat, P. Bhattacharya, R. Gupta and N. Kumar, *A taxonomy of energy optimization techniques for smart cities: Architecture and future directions*, Expert Syst. **39** (2022).

[33] K. Thangaramya, K. Kulothungan, R. Logambigai, M. Selvi, S. Ganapathy and A. Kannan, *Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT*, Comput. Netw. **151** (2019), 211–223.

[34] T. Yigitcanlar, M. Kamruzzaman, L. Buys, G. Ioppolo, J. Sabatini-Marques, E. Moreira da Costa and J. Joseph Yun, *Understanding 'smart cities': Intertwining development drivers with desired outcomes in a multidimensional framework*, Cities **81** (2018), 145–160.

[35] M. Zekić-Sušac, S. Mitrović, and A. Has, *Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities*, Int. J. Inf. Manag. **58** (2021), 102074.

[36] X. Zhang, G. Manogaran and B. Muthu, *IoT enabled integrated system for green energy into smart cities*, Sustain. Energy Technol. Assess. **46** (2021), 101208.

[37] S. Zhexuan, A. Cárdenas and R. Masuoka, *Semantic middleware for the Internet of things*, Internet Things (IoT), IEEE, 2010, pp. 1–8.

[38] X. Zhu, J. Wang, N. Lu, N. Samaan, R. Huang and X. Ke, *A hierarchical VLSM-based demand response strategy for coordinative voltage control between transmission and distribution systems*, IEEE Transactions on Smart Grid. **10** (2019), no. 5, 4838–4847.