Int. J. Nonlinear Anal. Appl. 15 (2024) 11, 131–138
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2023.31301.4610

Efficient energy management in a smart city based on multi-agent systems over the Internet of Things platform

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(Communicated by Seyyed Mohammad Reza Hashemi)

Abstract

The smart city model on multi-agent systems and the Internet of Things using a wireless sensor network is designed to improve the quality of life for citizens, increase resource efficiency, and reduce costs. This model enables the collection, analysis, and sharing of information by connecting and coordinating devices and systems within the smart city. In this model, intelligent agents act as sensors, and the smart gateway plays the role of a base station. The main goal of this model is to reduce energy consumption. To achieve this goal, intelligent agents are divided into clusters, with each cluster having a cluster head. The cluster head's task is to collect and aggregate information from the intelligent agents within its cluster and send it to the smart gateway. In the proposed method, each intelligent agent selects a cluster in a distributed manner. An intelligent agent may choose another intelligent agent as its cluster head or select itself as a cluster head and directly send the data to the smart gateway. Each intelligent agent chooses the cluster head after calculating the importance level of neighboring intelligent agents. By using this model, cities can experience increased resource efficiency and cost reduction by leveraging innovative technologies. The proposed method has been implemented in different scenarios of smart cities, such as sparse and crowded smart cities with varying message sizes. In all simulations, the proposed method demonstrated good capabilities in optimizing energy consumption management.

Keywords: Smart city, Energy consumption management, Intelligent agents, Clustering
2020 MSC: 68T05, 80M50

1 Introduction

Smart cities and the Internet of Things (IoT) enable the connection of various smart devices to interact with each other and external systems. In this system, home and office network devices such as smartphones, smart electronics, and set-top boxes connect to a network gateway. This gateway not only communicates with the local network but also manages the network of home and office devices. In a smart city, IoT devices connect to short-range networks to transmit data towards smart gateways. These short-range networks consume less energy compared to other networks.

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Received: July 2023 *Accepted:* December 2023

One of the most significant challenges that IoT has faced so far is the management of heterogeneity connected devices in this infrastructure. Consequently, the management of intelligent and autonomous mechanisms is a challenging task. However, using integrated software agents with IoT technologies provides an alternative solution to address this concern. The process of linking a software agent to each IoT object enables it to establish communication processes through the FIPA-ACL standard and thus allows the creation of distributed, independent, and heterogeneous IoT. In summary, agents are better technologies for creating smart objects compared to other approaches such as service-oriented and object-oriented paradigms [19].

The integration of agents and IoT is one of the factors that have led to the emergence of the Agent-based internet approach. Agent-based internet is proposed as an evolutionary process of IoT, where user participation in adapting the behavior of the IoT network through personalizing specific agents at runtime is essential. On the other hand, in the second perspective, agent-based Internet is considered as an intelligent ecosystem of agents that manages resources related to objects. To achieve this level of understanding, software agents that employ semantic contracts are introduced to IoT infrastructures. Consequently, areas, social loops, services, and IoT resources are managed. Additionally, researchers claim that by using these components in a compact and appropriate manner, the semantic descriptors present in agent contracts become inputs for reasoning processes, transforming connected objects in IoT networks into truly intelligent entities. Therefore, the capability of semantic collaboration is achieved by IoT systems [19].

Intelligent agents, as an abstraction layer in the Internet of Things, consist of software or intelligent programs that can modify their operations on various systems on behalf of their hosts. Agents utilize hosts as platforms for performing tasks such as data aggregation, energy management, data analytics, and computations. Compatibility, autonomy, distribution, asynchronous correlation, and scalability are some of the characteristics that intelligent agents bring to processing and computing systems. In recent years, intelligent agents have been used for energy management due to their ease of collaboration and intelligent decision-making capabilities [1, 12, 19].

Gateways typically act as hubs between sensor layers and cloud services. With a deep understanding of the role of gateways in smart buildings, where object mobility and location are limited to the building premises, it can be realized that the nature of gateways empowers them to handle the management of objects within the building in terms of processing power, power consumption, and communication bandwidth. Such valuable features can be leveraged by strengthening gateways with sufficient processing power, intelligence, and networking capabilities, resulting in a smart gateway [20].

Smart gateways take on the processing features and web-based software component [13, 14] for managing and transmitting signals related to applications. The smart gateway communicates with sensors inside the building. On the sensor side, the gateway is composed of data translation layers to receive information sent from various sensors that use different communication protocols. The gateway receives data from the sensors and performs network-level processing such as data aggregation, filtering, and dimensionality reduction.

A smart city model [15, 16] based on multi-agent systems over IoT and wireless sensor network is a novel approach in designing and managing cities. It aims to improve the quality of life for citizens, increase resource efficiency, and reduce costs. This model enables the connection and coordination between devices and systems in the city, allowing for the collection, analysis, and sharing of information.

A smart city based on multi-agent systems over the IoT can be effectively modeled as a network of wireless sensors. In this modeling, the sensor nodes act as intelligent agents, and the intelligent gateway can be considered as the base station. In this modeling approach, the sensors or intelligent agents are responsible for perceiving the environment.

The goal here is to reduce energy consumption. To achieve this, it is advisable to cluster the intelligent agents and select a cluster head for each cluster. The task of each cluster head is to collect information from the intelligent agents within the cluster and aggregate, compress, and transmit the data to the intelligent gateway (the base station).

The integration of wireless sensor networks with IoT brings about new applications in various aspects of life, enhancing human convenience. In wireless sensor networks, sensors operate with limited resources such as memory, processing power, and energy, while the IoT is equipped with abundant resources. It is crucial that the process of integrating wireless sensor networks with the IoT is carried out in a way that preserves the core capabilities of both networks and helps each other expand the scope of applications [24]. In this integration, there are several challenges such as connectivity and Infrastructure [3, 22], addressing [4, 5, 18, 23], protocols [8, 10, 11], nodes and data availability [9], and security [2, 7, 21, 25].

This paper is structured into five sections. The second section provides an overview of past methods and works. The section 3 describes the proposed methods. The section 4 presents the evaluation and results of the proposed method. Finally, the fifth chapter discusses the conclusions and future recommendations.

2 Proposed Method

In this paper, a distributed method is proposed for selecting an optimal cluster head for intelligent agents. The goal of this method is to increase the network's lifespan and manage the energy consumption of intelligent agents.

In the proposed method, each intelligent agent selects one intelligent agent as its cluster head in a distributed manner. An intelligent agent may choose another intelligent agent as its cluster head or select itself as the cluster head and directly send data to the intelligent gateway. After calculating the importance of neighboring intelligent agents in a distributed manner, each intelligent agent selects the cluster head.

Let's consider a smart city defined as a graph $G = (V, E)$, where V is the set of intelligent agents (the network nodes) and E represents the graph's edges. An edge $e = (u, v) \in E$ exists if and only if: a) $u \in V$, $v \in V$, and v is within the transmission range of u.The proposed method has six main steps that are listed below:

2.1 Step 1: Local view for an intelligent agent

The local view of a smart city from the perspective of an intelligent agent can be described as follows: a) The intelligent agent itself is included in the local view. b) All other intelligent agents within the transmission range of the agent are also included in the local view. c) Additionally, any intelligent agents that are within the transmission range of an agent, who is themselves within the transmission range of the original agent, are also included in the local view. d) The set of edges in the local view includes all possible edges between the agents in the local view, as long as those edges exist in the overall graph of the smart city. We denote the local view for intelligent agent v_i as $G_i(V_i, E_i)$ where V_i and E_i are the intelligent agents and edges, respectively.

2.2 Step 2: intelligent agent importance

The importance of an intelligent agent is indicated by its ability to act as an intermediary in transferring information between any two intelligent agents in a smart city. Therefore, the larger value shows the greater importance of the intelligent agent. Additionally, considering the local perspective of the intelligent agent, the larger this measure, the more it indicates that the intelligent agent can be connected to other intelligent agents through relatively short paths. The importance measure of intelligent agent v_i is calculated using the following equation:

$$IAI(v_i) = \sum_{u,v \in V_i, u \neq v \neq v_i} \frac{\rho_{uv}(v_i)}{\rho_{uv}} \tag{2.1}$$

where ρ_{uv} represents the number of shortest paths between two intelligent agents u and v. Note that the length of the shortest path between two intelligent agents u and v may be five, and there may be eight different paths of length five to reach from intelligent agent u to v. In this case, ρ_{uv} would be equal to eight. Furthermore, $\rho_{uv}(v_i)$ indicates the number of shortest paths between two intelligent agents u and v that pass-through intelligent agent v_i.

It is worth noting that ρ_{uv} cannot has a value of zero. Because there is at least one path between two intelligent agents u and v. Intelligent agent u is directly or indirectly connected to intelligent agent v_i with at most one intermediary intelligent agent. Similarly, node v is directly or indirectly connected to intelligent agent v_i with at most one intermediary intelligent agent. Therefore, there exists a communication path between the two intelligent agents u and v.

2.3 Step 3: candidate intelligent agents for cluster head

In this stage, intelligent agents are selected as candidates for clustering. Intelligent agent v_i receives the energy of all existing intelligent agents in the subgraph G_i through a message. Then, it considers agents whose energy is not less than the average energy of their neighbors as candidate intelligent agents for clustering. This stage is very important and has a significant impact on improving the performance of the proposed method.

2.4 Step 4: Selection of cluster head

In this stage, each intelligent agent considers one intelligent agent as its cluster head among the candidate intelligent agents, which has a higher importance in its subgraph. Let's assume IAI_i^j represents the importance of intelligent agent v_i for intelligent agent v_j. In this case, the variable representing the probability of selecting intelligent agent v_i as the cluster head for intelligent agent v_j is defined as follows:

$$p_i^j = \frac{IAI_i^j}{\sum_i IAI_i^j}. \tag{2.2}$$

In the next stage, intelligent agent v_j calculates the cumulative probability function as follows:

$$P_i^j = \sum_{k \le i} p_k^j. \tag{2.3}$$

In this stage, intelligent agent v_j generates a random number between zero and one. Then, the intelligent agent finds the first number in the P_i^j variable that is greater than the random number and selects the corresponding intelligent agent as the cluster head. To clarify the subject, let's examine it with a numerical example.

Suppose for intelligent agent v_1, there are four candidate intelligent agents named v_1, v_5, v_6, and v_7 with importance values of 2, 2, 5, and 1, respectively. The variables p_i^1 are given as follows:

$$p_1^1 = 0.2, p_5^1 = 0.2, p_6^1 = 0.5, p_7^1 = 0.1. \tag{2.4}$$

The cumulative probability function is calculated as follows:

$$P_1^1 = 0.2, P_5^1 = 0.4, P_6^1 = 0.9, P_7^1 = 1. \tag{2.5}$$

If the random number is 0.7, the first number greater than 0.7 corresponds to intelligent agent v_6. Therefore, intelligent agent v_6 is selected as the cluster head for node v_1.

2.5 Step 5: Data transferring

All intelligent agents are responsible for transferring their information to either a cluster head agent or an intelligent gateway. The energy needed to transmit k bits of data to an intelligent agent at a distance d can be calculated using the following formulas:

$$f(x) = \begin{cases} k(E_{elec} + \varepsilon_{fs}.d^2), & \text{if } d < d_0 \\ k(E_{elec} + \varepsilon_{mp}.d^4), & \text{otherwise} \end{cases}$$
$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{2.6}$$

Here, d_0 represents the threshold distance that determines which transmission model to use. If the distance is below the threshold, the free space model is employed; otherwise, the multi-path model is utilized. The coefficients in the equations are defined as follows:

- E_elec: The energy consumed by the transmitter per bit in nanojoules (nJ/bit).
- ε_{fs}: The energy dissipated per bit for driving the amplifier in the free space transmission model, measured in picojoules per square meter ($pJ/(m^2.bit)$).
- ε_{mp}: The energy dissipated per bit for driving the amplifier in the multi-path transmission model, measured in picojoules per fourth power of distance ($pJ/(m^4.bit)$).

The energy required to receive k bits of data can be calculated using the equation:

$$E_{RX} = k.E_{elec}. \tag{2.7}$$

Additionally, the energy consumed for aggregating m messages with a length of k bits can be calculated using the equation:

$$E_A = m.k.E_{DA}. \tag{2.8}$$

Here, E_{DA} represents the energy consumption for message aggregation in $nJ/(bit.signal)$.

2.6 Step 6: Return to the selection of a cluster for the next time period (Step 3)

After each time interval, each node reverts back to the third stage and continues the process.

3 Evaluation of the Proposed Method

An evaluation of the proposed method for a smart city with the specifications mentioned in the table 1 has been designed. Various experiments have been conducted with different numbers of intelligent agent. Additionally, the positions of the intelligent agents have been randomly placed in the environment.

The experiments were performed using Matlab2020 software on a computer with an Intel Core$i7-65002.59GHz$ CPU, $8GByte$ RAM, and Windows10 operating system.

The proposed method in this paper has been evaluated using four criteria: a) The time at which the first intelligent agent dies [6], b) The time at which the last intelligent agent dies [6], c) Energy remaining diagram and finally d) Active Agent Diagram or the number of active (alive) intelligent agents over time.

The proposed method was compared with three researches LEACH, LEACH-IoT 2019 [26] and LEACH-NI 2023 [17].

Table 1: Parameters of smart city

PARAMETERS	value
The size of a smart city's environment	$100100m^2$
Location of smart gateways	$(x, y) = (50, 50)$
Number of intelligent agents	50
Size of messages	$2000bits$
Threshold distance	$d_0 = 87.7058m$
Initial energy of intelligent agents	$2J$
E_{elec}	$50nJ/bit$
ε_{fs}	$10pJ/(m^2.bit)$
ε_{mp}	$0.0013pJ/(m^4.bit)$
E_{DA}	$5nJ/(bit.signal)$

In this section, the proposed method applied on the smart city described in the above table and the results have been evaluated by considering two measures: the average energy usage of the smart city at any given moment (Figure. 1) and the number of intelligent agents currently operational (Figure. 2).

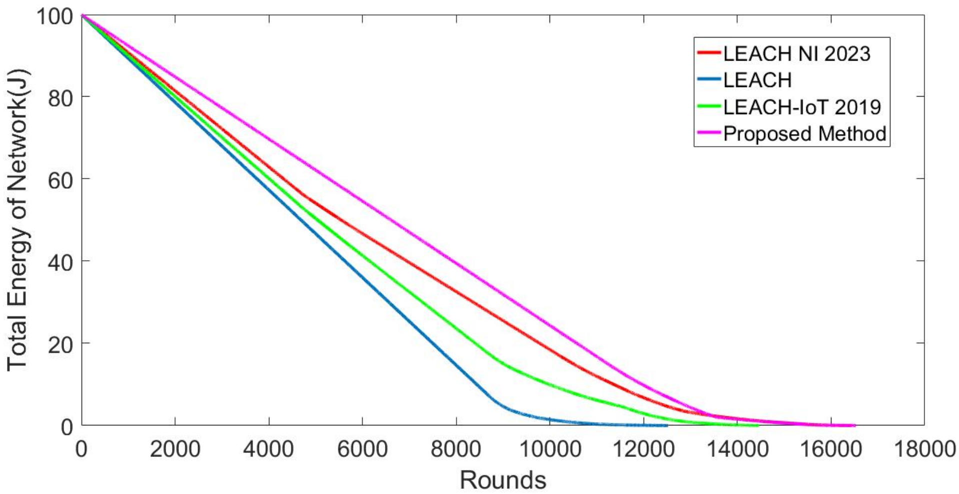

Figure 1: Energy Remaining Diagram for The Network with 50 Agents

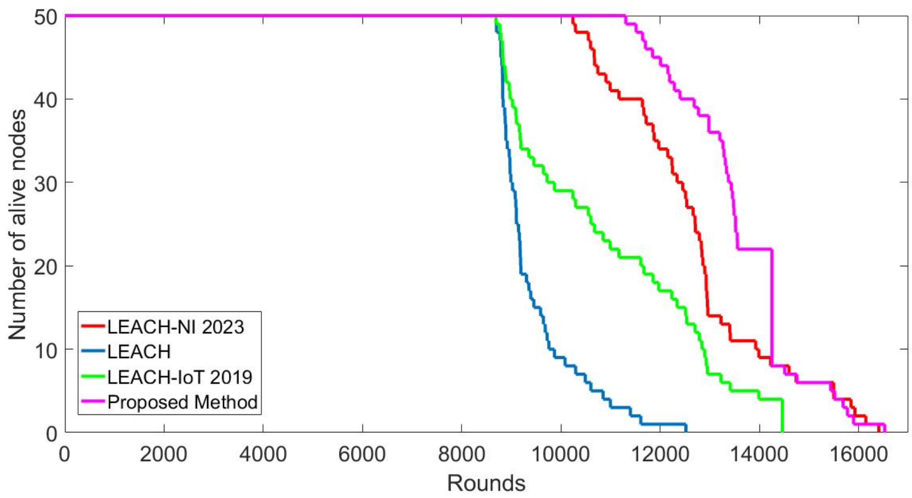

Figure 2: Number of Alive Intelligent Agents over Time for The Network with 50 Agents

In this section, the time of the first death of an intelligent agent in the smart city has been evaluated. The evaluation has been conducted for various values of the initial number of intelligent agents in the network. In all cases, the proposed method performs better than the other methods (Figure. 3).

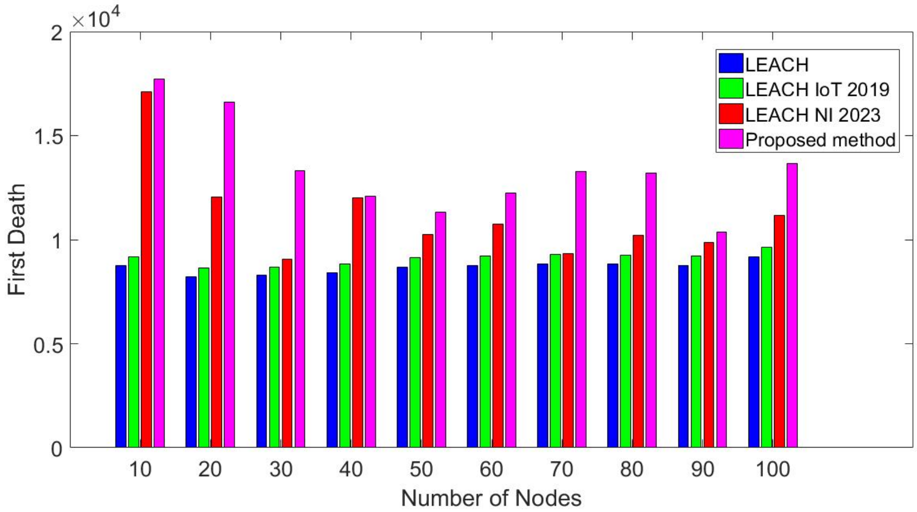

Figure 3: The time of death of the first artificial intelligence agent

In this section, the time of the last death of an intelligent agent in the network has been evaluated. In other words, this is the time when the last remaining intelligent agent in the city also loses its energy and the entire network collapses. The evaluation has been conducted for various values of the initial number of intelligent agents in the network. In all cases, the proposed method performs better than the other methods(Figure. 4).

4 Conclusion

In a smart city, internet of things uses short-range networks to transfer data to smart gateways, which are responsible for local network communication and managing network devices. The proposed method for energy management in a smart city involves using intelligent agents and internet of things networks. This model enables the collection, analysis, and sharing of information between devices and systems in the city, aiming to reduce energy consumption. The method utilizes multi-agent systems and internet of things to improve energy management, leading to enhanced quality of life, increased resource efficiency, and cost reduction. This paper presents a distributed method executed

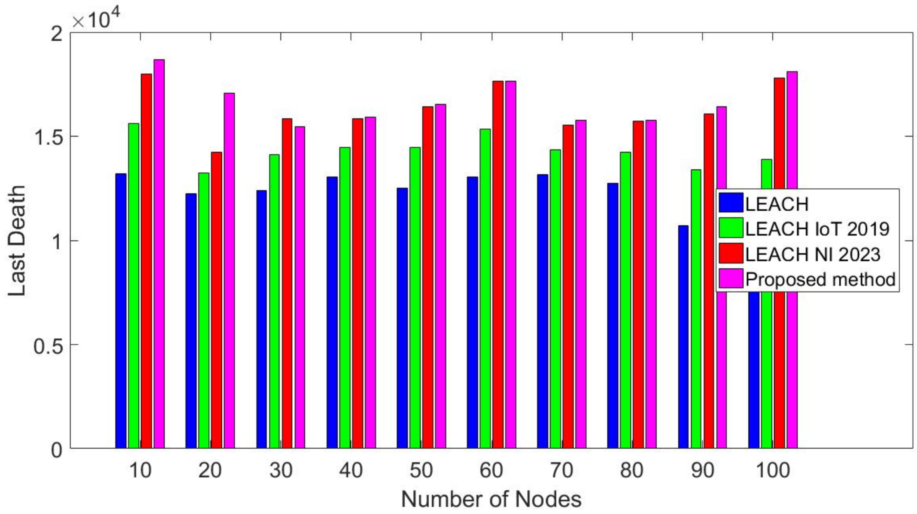

Figure 4: The time of death of the last artificial intelligence agent

by each intelligent agent, which has been evaluated in different scenarios, demonstrating its effectiveness in energy management.

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