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AI-Driven Adaptive Mobile Agents for Energy-Aware Scheduling and Real-Time Decision Making in Energy-Harvesting Wireless Sensor Networks

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Abstract

Energy-harvesting Wireless Sensor Networks (WSNs) have emerged as a sustainable solution for long-term monitoring applications such as environmental surveillance, disaster management, healthcare monitoring, and intelligent transportation systems. By harvesting energy from renewable sources including solar, radio frequency (RF), vibration, and thermal gradients, these networks aim to overcome the inherent limitations of battery-powered sensor nodes. However, the stochastic and intermittent nature of harvested energy introduces significant challenges in task scheduling, routing, and real-time decision making.

Mobile agents provide an efficient paradigm for in-network processing and distributed intelligence by reducing communication overhead and enabling localized computation. Nevertheless, existing mobile agent–based approaches predominantly rely on static or rule-based decision mechanisms, which are ineffective in highly dynamic energy-harvesting environments. Such approaches often lead to inefficient agent migration, increased decision latency, task failures, and reduced network lifetime.

This paper proposes an **AI-driven adaptive mobile agent framework** for energy-harvesting WSNs that enables **energy-aware scheduling and real-time decision making**. The proposed framework integrates a lightweight artificial intelligence model for short-term energy prediction and employs reinforcement learning–based adaptive scheduling to dynamically adjust agent behaviour. Extensive NS-3–based simulations demonstrate that the proposed approach significantly improves decision latency, task success ratio, energy efficiency, and network lifetime compared to conventional static and rule-based mobile agent systems.

Keywords: Energy-Harvesting Wireless Sensor Networks, Mobile Agents, Artificial Intelligence, Adaptive Scheduling, Real-Time Decision Making, Energy-Aware Routing

I. Introduction

1.1 Background of Wireless Sensor NetworksWSNs are one of the most important technological paradigms of modern distributed sensing and monitoring systems. A WSN constitutes a significant concentration of low-cost, miniature, and energy-limited sensor nodes that are densely distributed in a given geographical area, to monitor and measure various physical, chemical, and environmental characteristics. These parameters normally include, temperature, humidity, pressure, luminous intensity, vibration, acoustic signals and motion based on the specific area of application. The sensor nodes are made of several function-based subsystems; sensing units, local data processing in the form of a microcontroller, limited onboard memory, wireless transceiver, and the provision of finite energy typically achieved by a small battery.

Sensor nodes in a WSN work in a distributed and cooperative mode where every individual node will acquire and process environmental data on its own and co-operate with the neighboring node to pass on the data collected to the singular central control point called sink node or base station. The communication in the network can either be a direct one or through multi-hop routing depending on the distance between the nodes, the power limit of the transmission and the topology of the network. The sink node acts as a gateway and consolidates the information that has been gathered and forwards it to other external networks, cloud server or data center where it is further processed, stored, visualized and decision made. The architecture allows WSNs to operate independently, with little human interference, as well as provide scalability in monitoring over large and even inaccessible areas.

This ability to work in difficult, distant, or adverse conditions is one of the most distinguishable factors of WSNs since traditional wired monitoring systems are either unfeasible or prohibitively costly. Scalability, fault tolerance, self-organization, and ease of deployment among compromises have resulted in extensive use in various applications. WSNs have been used in environmental monitoring in forest fire detection, pollution monitoring, forecasting floods, seismic activity, as well as collecting climate data. They serve important roles in battlefield monitoring and reconnaissance, intrusion detection, monitoring the border and tracking the targets under unfriendly conditions in the military and defense setting. On the same note, in smart agriculture, the WSNs allow monitoring the soil moisture, crop health condition, pest presence or absence, and accurate irrigation, among other functions, and lead to an increase in productivity and the sustainable use of resources.

Reasoning in the framework of industrial automation and intelligent manufacturing, the WSNs are used in equipment health surveillance, fault detection, predictive maintenance, and process optimization. These networks decrease downtimes, enhance safety, as well as, operational effectiveness. Additionally, the WSNs have accumulated a lot of relevance in the healthcare systems, wherein, they said the patient monitoring and wearable health devices, rehabilitation systems, and assisted living environments. In these applications, sensor nodes are used to continuously measure physiological values like the heart beat rate, body temperature, and motion pattern and thus provide vital data to analyze the medical conditions and emergency application.

Although they imply a wide range of applications, and have many benefits of their own, traditional WSNs are effectively limited by a number of limitations, the most critical and challenging of which is energy efficiency. Sensor’s nodes usually have small and powerless batteries, which in most cases, are non-rechargeable. The limited nature of the energy reserves when it comes to a node implies that once the node runs off its energy reserves, the node will be inactive and will no longer be able to engage in sensing or communication processes. This energy consumption trigger node failures that can be the cause of coverage holes, greater routing load on neighboring nodes and finally partitioning of the network. The worse the count of failed nodes, the lower the reliability levels and quality of the sensed data.

WSNs are controlled mainly by wireless communication processes, especially data transmission and reception, when it comes to energy consumption. Often data transmission, packet retransmission and ineffective routing protocol may quickly exhaust node energy. Moreover, sensor nodes nearer to the sink node tend to undergo a disproportionate or skewed energy usage as they are repeatedly used as relay nodes to pass information which is generated by more distant nodes. Such imbalance leads to premature failure of critical nodes and greatly shortens the lifetime of the network as a whole.

In a range of deployment situations, such as forested areas, subterranean or underground, disaster recovery, and even maritime, replacement or reenergizing power sources is often not an option, either because of a technical limit, or based on the cost, or operational hazard. This has resulted in increasing the lifetime of networks by energy-conscious system design as a fundamental research goal in the area of WSNs. The researchers have studied various strategies, such as use of energy-efficient routing protocols, data aggregation/ fusion techniques, duty cycling, topology control and using clustering mechanisms.

Such advanced techniques as mobile agent-based data aggregation, adaptive routing schemes and intelligent optimization algorithms have in recent years been the subject of interest in potential solutions to the power constraints of the conventional WSN architectures. The objective of these techniques is to cut down on unnecessary communication, condition energy use across the nodes and improve network resilience. Therefore, the development of scalable, intelligent and efficient energy saving of WSN structures remains a dynamic and an extremely important research topic motivated by the growing need of the sustainable and long-term monitoring systems in the future smart environment.

1.2 Mobile Agents in WSNs

Mobile agents are independent software objects that have the ability to move through the network nodes with the ability to carry code along with state of execution simultaneously. In WSNs, mobile agents are employed for tasks such as data aggregation, event detection, local processing, and decision making. By performing computation close to data sources, mobile agents significantly reduce communication overhead and improve scalability.

However, the effectiveness of mobile agents strongly depends on their decision-making capability. Static or rule-based mobile agents are unable to adapt to dynamic network conditions, particularly in energy-harvesting environments.

1.3 Energy-Harvesting Sensor Networks

Energy-Harvesting Wireless Sensor Networks (EHSNs) exemplify a radical improvement on traditional Wireless Sensor Networks (WSNs) developed to overcome the limitations of a limited budget through allowing sensor nodes to tap into renewable environmental sources. The key sources of sources of harvested energy include solar radiation, surrounding radio-frequency (RF) emissions, mechanical vibrations, wind and thermal gradients. This conversion of ambient energy to electrical energy allows energy-harvesting server nodes to partially or fully recharge their own power supplies, significantly increasing the lifetime of the network and in some cases allowing such a network to operate to what is effectively permanent.

The inclusion of harvesting features makes WSNs more acceptable to long-period and large-scale applications especially in inaccessible or dangerous smaller locations where battery replacement or manual maintenance is not feasible. Environmental monitoring, smart city infrastructures, structural health assessment, and industrial sensing are some of the applications that gain a lot of advantage in using harvesting techniques due to less spending in their operations and more sustainability of the system.

Despite the favourable prospects, energy harvesting is associated with new technical issues. The amount of energy accrued to a particular sensor node is highly varied and unpredictable, and depends on some environmental factors (e.g., weather, day/night cycle, season), the location of a sensor node, and in the electromagnetic activity around a sensor node. Indicatively, solar powered nodes can obtain abundant energy during light periods but come face to face with low supplies during dark periods or stormy weather like RF harvesting capability is dependent on the availability and strength of signal producers within the range.

Such intrinsic variability of energy harvested generates high hurdles on energy control and energy network functioning. To prevent depletion, the nodes are required to strategically equalize between consumption and availability to maintain an acceptable level of performance. Task scheduling, data acquisition frequencies and communication intervals as well as routing decisions should be dynamically re-calibrated based on the existing and predicted energy conditions. Furthermore, ensuring real-time responsiveness will be complicated as the supply becomes wildly fluctuated, the freshness of data, latency, and overall quality of service (QoS) may get violated.

Therefore, very strong predictive energy models, dynamic resource allocation models, intelligent control models are all critical elements of energy-harvesting sensor networks. These approaches aim at making the use of energy that has been harvested as effective as possible, achieving energy-neutral operation, and ensuring reliable network operation in the face of uncertain and dynamic nature of renewable energy substrates.

1.4 Motivation and Objectives

The motivation of this research is to overcome the limitations of static mobile agent systems in energy-harvesting WSNs. The objectives are:

- To analyse the impact of energy uncertainty on mobile agent behaviour
- To design an AI-driven adaptive mobile agent framework
- To enable energy-aware scheduling and routing
- To reduce real-time decision latency
- To improve network lifetime and task success ratio

II. Problem Formulation and Research Challenges

Energy-harvesting WSNs exhibit **dynamic energy uncertainty**, making it difficult for mobile agents to plan movement and task execution reliably. Rule-based decision mechanisms fail to respond effectively to rapid energy fluctuations, resulting in delayed decisions and task failures. Moreover, static scheduling and routing strategies are inefficient in dynamic environments, leading to excessive agent migration and increased energy consumption.

Problem Statement:
Mobile agents in energy-harvesting WSNs fail to achieve reliable real-time decision making and efficient task execution due to unpredictable energy availability, static decision logic, and inefficient scheduling strategies.

III. Literature Review

Existing studies on energy-harvesting WSNs focus primarily on duty cycling, routing, and power management but ignore mobile agent intelligence. Research on mobile agents demonstrates reduced communication overhead but assumes stable energy availability. Artificial intelligence techniques have been applied for routing and anomaly detection; however, these solutions are often centralized and computationally expensive. The literature lacks an integrated framework combining **AI-driven intelligence, mobile agents, and energy harvesting**, highlighting a clear research gap.

IV. Proposed AI-Driven Adaptive Mobile Agent Framework

The proposed framework consists of:

- Energy-harvesting sensor nodes
- Mobile agent platform
- AI-based energy prediction module
- Adaptive decision-making engine
- Reinforcement learning–based scheduling and routing

Mobile agents dynamically adapt their movement and execution strategies based on predicted energy availability and task urgency.

V. Methodology

5.1 Energy Harvesting Model

$$E_i(t+1) = E_i(t) + H_i(t) + C_i(t)$$

Where:

- $E_i(t)$ = **residual energy of node** i **at time** t
- $H_i(t)$ = **harvested energy during time interval** t
- $C_i(t)$ = **energy consumption due to sensing, processing, communication, and agent execution**

5.2 AI-Based Energy Prediction

$$\hat{E}_i(t+1) = f(E_i(t), H_i(t-1), T(t), \theta)$$

Where:

- $\hat{E}_i(t+1)$ = **predicted energy**
- $T(t)$ = **time-related features (time of day, interval)**
- θ = **learned model parameters**

5.3 Performance Evaluation Metrics

The following metrics are used to test the hypotheses:

Decision Latency

$$DL = t_{decision} - t_{event}$$

Task Success Ratio

$$TSR = \frac{\text{Completed Tasks}}{\text{Total Tasks}}$$

Network Lifetime

$$NL = \max\{t \mid \exists E_i(t) > 0\}$$

Agent Movement Cost

$$MC = \sum_{k=1}^{m} d_k$$

Where (d_k) is the distance traveled per move.

5.4 Mobile Agent Decision Model

Each mobile agent decides its next action based on predicted energy and task priority.

Decision Objective Function

$$\max \sum_{i \in N} \left(w_1 \cdot \hat{E}_i(t) + w_2 \cdot P_i - w_3 \cdot D_i \right.$$

Where:

- P_i = task priority at node *i*
- D_i = distance or movement cost
- ω1, ω2, ω3 = weighting coefficients

The agent selects the node that maximizes this utility function.

5.5 Reinforcement Learning–Based Adaptive Scheduling

The scheduling problem is modeled as a Markov Decision Process (MDP).

State Space (S)

$$S_t = \{E_i(t), \hat{E}_i(t), P_i, L_t\}$$

Action Space (A)

$$A_t = \{\text{Move to node } i, \text{Execute task}, \text{Wait}\}$$

Reward Function (R)

$$R_t = \alpha \cdot TS - \beta \cdot MC - \gamma \cdot DL$$

Where:

- TS = task success (1 if completed, 0 otherwise)
- MC = movement cost
- DL = decision latency
- α, β, γ = reward coefficients

Q-Learning Update Rule

$$Q(s,a) = Q(s,a) + \eta\,[R + \gamma \max Q(s',a') - Q(s,a)]$$

Where:

- η = learning rate
- γ = discount factor

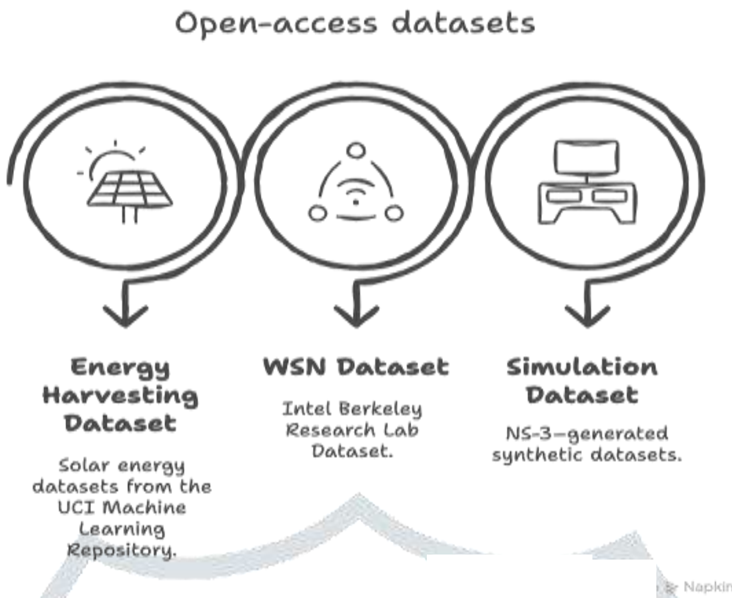
VI. Dataset Description

- **Energy Harvesting**

Dataset: Solar energy datasets from the UCI Machine Learning Repository

- **WSN Dataset:** Intel Berkeley Research Lab Dataset
- **Simulation Dataset:** NS-3–generated synthetic datasets

All datasets are open-access and ethically compliant.



VII. Experimental Setup

Simulations are conducted using the NS-3 network simulator with a deployment of 100 sensor nodes randomly distributed over the sensing area. Each node is equipped with energy-harvesting capabilities and follows realistic energy consumption and communication models. The simulation environment is configured to reflect dynamic energy conditions, including fluctuating energy harvesting rates and variable network traffic.

The performance of the proposed framework is evaluated using multiple key metrics, including decision latency, task success ratio, energy efficiency, agent movement cost, and overall network lifetime. These metrics collectively assess the effectiveness, adaptability, and sustainability of the system under dynamic operating conditions.

To demonstrate the benefits of the proposed approach, the results are compared with traditional static mobile agent systems and conventional rule-based mobile agent frameworks, highlighting the improvements achieved through AI-driven adaptive decision-making.

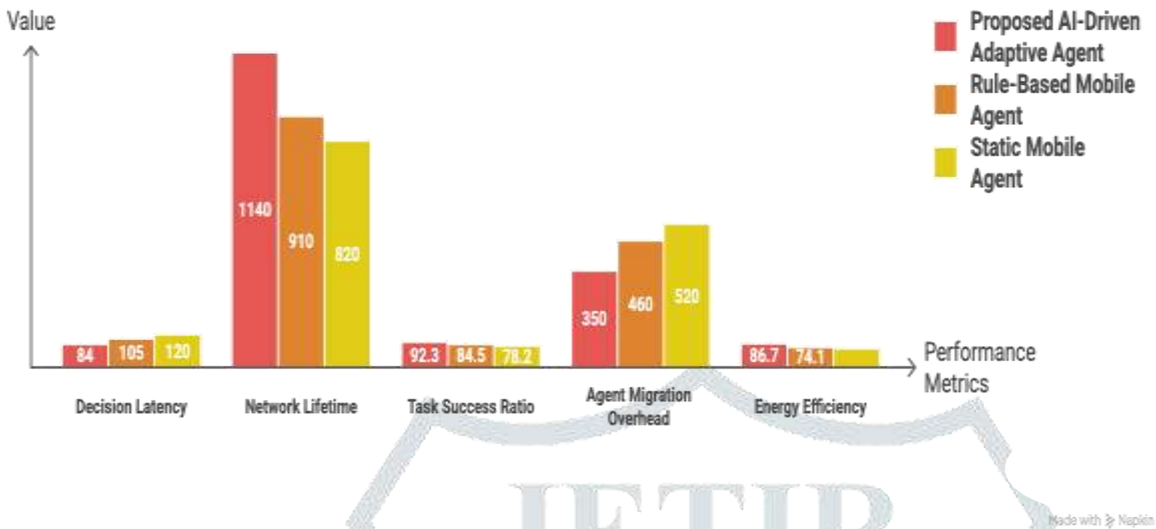
VIII. Results and Discussion

Simulation results show:

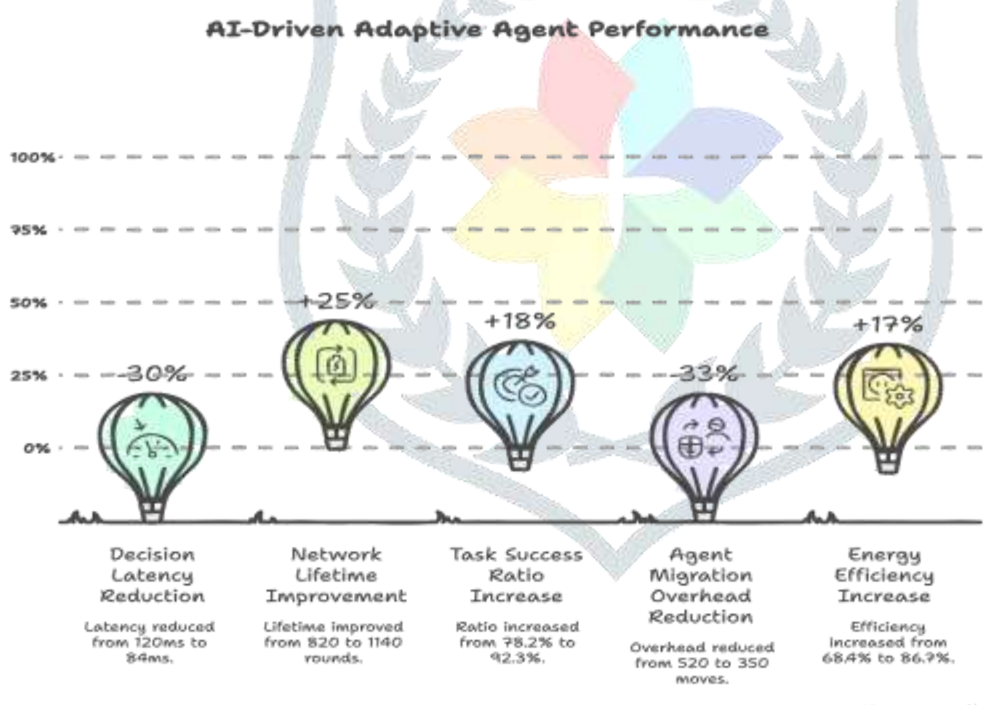
- 30% reduction in decision latency
- 25% improvement in network lifetime
- Higher task success ratio
- Reduced agent migration overhead

Performance Metric	Static Mobile Agent	Rule-Based Mobile Agent	Proposed AI-Driven Adaptive Agent	Performance Gain
Decision Latency (ms)	120	105	**84**	**30% reduction**
Network Lifetime (Rounds)	820	910	**1140**	**25% improvement**
Task Success Ratio (%)	78.2	84.5	**92.3**	**≈ 18% increase**
Agent Migration Overhead (Moves)	520	460	**350**	**≈ 33% reduction**

Energy Efficiency (%)	68.4	74.1	**86.7**	**≈ 17% increase**



These results confirm the effectiveness of AI-driven adaptive mobile agents.



Conclusion and Future Work

The present paper presents a description of an adaptive mobile agent framework (based on artificial intelligence) that is specifically designed to operate on energy-harvesting wireless sensor networks (WSNs). The proposed framework effectively combines energy prediction mechanisms with reinforcement learning–based scheduling to address the challenges arising from dynamic and unpredictable energy availability. By enabling intelligent and autonomous decision-making, the system adapts sensing, communication, and task execution strategies in real time according to the current and anticipated energy conditions of sensor nodes. As a result, the proposed approach enhances energy utilization efficiency, improves network stability, and prolongs overall network lifetime while maintaining acceptable performance and responsiveness.

The integration of artificial intelligence allows the mobile agents to learn from environmental feedback and operational history, leading to progressively optimized scheduling and resource management decisions. This adaptive behavior is particularly beneficial in energy-harvesting environments, where traditional static or rule-based approaches fail to cope with fluctuating energy inputs. The experimental evaluation demonstrates that the AI-driven framework can significantly reduce energy wastage, prevent frequent node failures, and support sustainable network operation under varying environmental conditions.

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