# A paradigm shift toward intelligent packet routing for mobile IoT networks using deep learning

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***Abstract*—The proliferation of Internet of Things (IoT) devices has resulted in a deluge of data, significantly impacting the performance of IoT services and networks. Among the critical components of networking, packet routing plays a key role in facilitating the transfer of data packets within interconnected IoT networks. Traditionally, conventional proactive and reactive routing protocols rely on neighbor information and control messages to construct a comprehensive network view. They then calculate optimal paths to reach their destinations. Once data packets are delivered, any record of past routing decisions is discarded, and only current information is considered when determining new routes. In our ongoing research, we propose the application of a deep Learning approach to harness the knowledge gained from previously successful routing decisions. This enables the creation of new decision models, which nodes within the network can utilize to make intelligent routing choices.**

***Index Terms*—Deep Learning, Internet of Things, Mobility, Optimization, Routing.**

## I. Introduction

The Internet of Things (IoT) represents a paradigm shift in the way we perceive and interact with the world around us. It is a transformative vision where nearly every physical object, from household items and vehicles to industrial machinery and urban infrastructure, becomes digitally connected to the internet. This interconnected web of ”things” generates a vast ecosystem of smart devices that can collect, share, and analyze data. These devices have the potential to enhance our daily lives in countless ways, from optimizing energy consumption in our homes to improving transportation systems, healthcare delivery, and environmental monitoring. IoT holds the promise of creating a more efficient, intelligent, and interconnected world where data-driven insights and automation play a central role in shaping our future.

The pervasive nature of IoT is reshaping industries across the board. In agriculture, IoT sensors monitor soil conditions and crop health, enabling precision farming and sustainable practices. In healthcare, wearable devices and remote monitoring systems provide real-time health data, empowering individuals and transforming patient care. Manufacturing and logistics benefit from IoT-driven supply chain optimization and predictive maintenance. Smart cities leverage IoT for traffic management, waste reduction, and enhanced public services. Moreover, IoT's influence extends to consumer goods, enabling smart homes, connected vehicles, and personalized shopping experiences. As IoT continues to evolve, its transformative power is evident in nearly every facet of our lives, ushering in an era of unprecedented connectivity and innovation.

The proliferation of connected devices, driven by the Internet of Things (IoT), has brought about a remarkable upsurge in the amount of data being generated. This data explosion is especially pronounced in the realm of smart cities, where various sensors, cameras, and interconnected systems continuously collect and transmit information. These data volumes in smart cities tend to experience rapid growth as urban areas adopt more IoT technologies for improving services, infrastructure, and sustainability. However, it's crucial to recognize that IoT devices, despite their instrumental role in data collection, often operate under significant constraints. These constraints encompass limitations in processing power, which means they can't perform complex computations as conventional computers can. Additionally, IoT devices typically have restricted memory capacities, restricting their ability to store large datasets. Moreover, energy resources are finite for many IoT devices, necessitating power-efficient strategies to prolong device lifespans and minimize maintenance.

Given these inherent constraints, the development of efficient routing protocols is imperative. These protocols are essential for ensuring that data is transmitted optimally within IoT networks, taking into account the limitations of individual devices. By doing so, we can maximize the utility of IoT technologies while mitigating resource wastage and optimizing the performance of smart city systems. This task of crafting routing protocols tailored to the unique challenges of the IoT ecosystem is increasingly vital as IoT adoption continues to expand across various industries and applications.

In the current Mobile Ad Hoc Network (MANET) routing protocols, the process of establishing routes relies on broadcasting control packets during the initial path discovery phase and periodically sending HELLO packets during route maintenance. However, these protocols lack the ability to take into account the real-time routing context and past routing experiences. Consequently, the protocol essentially repeats the same procedures within the same context to achieve the same outcome, without capitalizing on its prior routing decisions or employing artificial intelligence techniques to enhance performance. In summary, traditional routing protocols lack intelligence; they lack awareness of the prevailing context and do not consider previous routing choices made.

In the context of smart cities, people's everyday movements often follow a consistent pattern, characterized by repetitive routines and actions. For instance, individuals may take the same route to school on a daily basis. Many prior studies, including references [1], [2], and [3], leverage this predictability in mobility to address issues related to forecasting the positions of nodes at various time intervals. Hence, we concur that predictable movements among network components are indeed prevalent, particularly within contemporary urban environments.

Despite the typical predictability in the movements of mobile nodes, previous research has not taken this factor into account when choosing the next hop node. Consequently, our proposed solution involves the utilization of a deep learning method to harness the consistency exhibited by mobile components in order to enhance the efficiency of routing protocols.

In the literature, various studies have employed deep learning methods to address routing problems, highlighting their significant potential to enhance network performance.

In their work, as described in [4], the authors introduce an intelligent network traffic control method to address a common problem with conventional routing protocols. the problem is that traditional routing protocols often fail to adapt and learn from past experiences, especially regarding network anomalies like congestion. To tackle this issue, the authors propose a novel real-time traffic control approach based on deep learning. This method utilizes deep Convolutional Neural Networks (deep CNNs) with unique inputs and outputs designed to represent the Wireless Mesh Network (WMN) backbone effectively.

In the realm of Underwater Acoustic Sensor Networks (UASNs), challenges such as long latency, high energy consumption, and dynamic network topology have persisted. To address these issues, the authors of this paper [5] introduce an adaptive routing protocol named Deep Q-Network-based Energy and Latency-Aware Routing (DQELR). DQELR employs a Deep Q-Network algorithm that combines off-policy and on-policy methods to make globally optimal routing decisions.

The remainder of this paper is structured as follows. Section 2 presents a brief description of the proposed solution. Section 3 presents the results and discussions. Finally, Section 4 presents the conclusion of this work.

## II. Proposed Solution

In our work, we aim to create a framework that allows participant nodes in IoT networks to intelligently route data packets. This involves reducing the need for nearby communication with neighboring nodes during route discovery and maintenance operations. To achieve this, nodes should learn from their previous routing decisions while on the move and transmitting data packets over time. We suggest predicting the next hop for packet forwarding by leveraging the regularity observed in the movement of mobile nodes. Ultimately, our objective is to minimize the use of traditional routing protocols in favor of deep learning techniques. We outline our framework in three main phases, as shown in Figure 1.

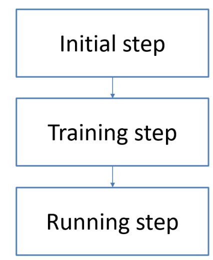


Fig. 1. The system model

Below, we will provide an explanation of the three phases.

### A. Initial Step

In this phase, we save all information concerning a successful routing decision of a data packet in a dataset, this is happened at each node. Usually, the routing decisions rely on a routing protocol, which is used to find the best path that packets should traverse, starting from a source node, and ending at the destination node. The routing protocols are used at each node to decide the next hop the packet should be forwarded to reach the final destination. Furthermore, concerning mobile networks, mobile nodes change their zone of existence at different moments. Therefore, the predictability of nodes' routing decisions is time-space and local context varying.

From the routing protocols analysis, we based our proposition on using the following information to be saved after a successful routing decision:

- Actual node: represents the current node with the data packet and seeks to forward it.
- Source node: represents the source node that initiates transmitting the data packet. The source and actual nodes are the same at the first transmission.
- Destination node: represents the final destination that the source node wants to send its data packet.
- Actual neighbours: this is a piece of local-context information. It represents all nodes that exist on the transmission range of the actual node.
- Time: presents the time, the day of the week, the day of the month, and the month at which the successful routing decision is made. Such information can represent the regularity and periodicity of the routing decision made. For example, a specific next hop is always chosen on Saturday afternoon.
- Actual Position: represents the geographical position of the current node when taking the routing decision.
- Next-hop: represents the routing decision to which the actual node decided to send its data packet

After gathering a sufficient amount of data from each node, a set of datasets is constructed as the outcome of this phase.

| Day | Current time | Current node | Destination node | Next-hop |
|---|---|---|---|---|
| 1 | 5.012556 | 30 | 1 | 21 |
| 1 | 5.03836 | 21 | 1 | 10 |
| 1 | 5.043253 | 10 | 30 | 21 |

Fig. 2. Sample of our gathered dataset

*B. Training step*

The resulting datasets are used to construct decision models. We seek to build a classifier for each of the participant network nodes, that is used to recognize the suitable node, among its neighbour nodes, that should be selected as a next-hop node. Since nodes do not have enough resources, the gathered datasets are sent to a dedicated server equipped with high storage and computing capacities.

*C. Running step*

In this phase, every node relies on its built model instead of the routing protocol to determine how to route data packets. This model is essentially a function that takes into account factors like time, node-specific data, and the characteristics of the packet itself. It then uses this information to determine the next hop or node where the data packet should be sent. If this decision model is unable to correctly route the data packet to its intended destination, the node must revert to using the original routing protocol to attempt to resend the packet.

## III. Results and discussion

In this section, we present the validation of our proposed solution.

*A. Initial Step*

The initial step involves gathering data about successful routing decisions made by each node in a dataset. To achieve this, we established a network of nodes and selected a suitable mobility model. We conducted simulations using the NS-2 simulator along with the AODV routing protocol, during which we recorded information related to successful routing decisions over a period of time. This recorded data is categorized into four key features: Day, Current time, Current node, Destination node, and the Nexthop category as shown in Figure 2. Importantly, the number of categories in the dataset matches the number of nodes in the network. Ultimately, we amassed a dataset containing 16,384 samples collected from all the nodes.

*B. Training step*

In the training process of our model, we employ a Recurrent Neural Network (RNN) with a many-to-one architecture as depicted in Figure 3. This specific RNN configuration plays a pivotal role in our model's functionality. It enables us to process sequential data efficiently, with the 'many-to-one' design signifying that it can handle input sequences of varying lengths and produce a single output, making it particularly suitable for tasks such as sequence classification or prediction. This architecture ensures that our model can effectively learn and capture patterns, dependencies, and temporal information within the input data, allowing it to make accurate predictions or classifications based on the learned context.

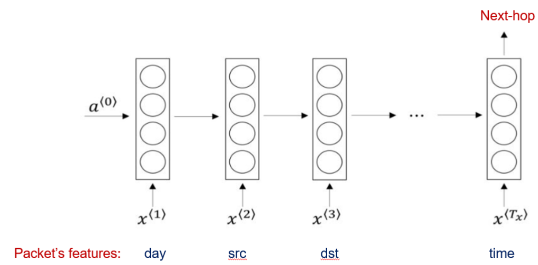


Fig. 3. RNN model using many to one architecture

Our proposed RNN model was implemented in python using the numpy library

*C. Evaluation*

In order to evaluate the efficiency of our RNN model, we will compare it with the AODV protocol in terms of the total number of sent packets transmitting N DATA packets from their sources to their destinations. The accuracy obtained from our model is p= 0.72 %, which means that p × N data messages will be correctly transmitted from their sources to their destinations.

## IV. Conclusion

In this paper, we introduced a deep learning approach aimed at enhancing routing efficiency within mobile IoT networks. Our primary emphasis was on networks with consistent and recurrent mobility patterns. Our novel protocol revolves around the prediction of the next routing step without direct communication with neighboring nodes, leveraging the capabilities of Recurrent Neural Networks (RNN). The protocol starts by recording routing decisions within the network and subsequently employs this historical data to construct predictive models for determining next-hop destinations during future routing tasks.

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