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Machine Learning for Routing in IoT: A Review

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Abstract. Internet of Things (IoT) knows a widespread adoption nowadays and provides many fascinating applications such as smart houses, smart cities, and intelligent healthcare. This technology tries to connect all habitual objects in daily life through the internet. Thus, creating many challenges to existing networking solutions. In this context, routing algorithms need to be improved to deal with new challenges such as a large number of nodes, limited supply, storage, and processing resources. On another side, researchers use machine-learning techniques to improve many tasks using artificial intelligence. In this paper, we study the IoT routing algorithms and usage-of machine learning techniques for their optimization. We will present IoT's principles, applications, and challenges. Then, routing protocols for IoT and their limits. Finally, we review proposed routing solutions using machine learning techniques and their achieved results.

Keywords and phrases: IoT, Routing, Machine Learning, Mobile networks.

1 Introduction

Internet of things has become popular and gained more interest from researchers and even end-users. This rise of attention happens due to the offered possibilities to integrate anything or any physical devices into the world of communication, thus creating connected things that provide services via the internet, which will improve the quality of life.
The ability to connect anything to the internet opens up opportunities to develop a new and large number of applications. Accordingly, hundreds of billions of devices will be connected throw the internet. As a result, from one side, a large amount of data from these devices will be

generated to be transferred (which imposes an overhead on the routers). On another side, the conditions where these devices and routers are acting, are different from other networks: such as mobility of devices, their limited resources, limited bandwidth, overhead, lower processing capacities, which raises new routing challenges in the IoT networking field.

Routing is the process of selecting paths to route data traffic, sent from a source node to an ultimate destination, by the mean of routing protocols. Existing routing solutions for mobile routing (such as AODV) are not adequate and need to be improved to face such new conditions. The new proposed solutions have to decrease the charge of making routing decisions by the routers. Hence, machine learning can help routers to learn from their experience, and avoid doing complex routing decisions, each time they need to route a packet.

Machine learning is an artificial intelligence technology. It is a set of techniques that enable computers (any computing devices) to learn without being explicitly programmed.
Indeed, machine learning techniques are used extensively in many networking fields to help decision making. This fact inspired us to develop machine learning-based solutions to improve the routing task in the IoT.

The remainder of this paper is organized as follows: Section 2 provides an overview of the internet of things, to draw the big picture of this technology. In section 3, we explain the classification of routing protocols used in IoT. In section 4, we define machine learning and its learning paradigms, to distinguish where to use one technique over another. In section 5, we present some reviews from the literature and recap some works that use the learning paradigms in solving different routing issues.

2 Internet of things

Originally, the term Internet of Things "IoT" was first used by Keven Ashton back in 1999 [1], but an exact definition has not yet been presented. It can be considered as a new revolution of the Internet's application that aims to skip the old fashion of connecting only the computing devices to the internet, to encompass the connection of all the physical devices to or through the internet [2]. A closer look at this phenomenon reveals the spotlighting of two important features, being an "internet" application, and dealing with the "thing's" information [3].

The “Things” notation is used to include a more generic set of entities and can be anything (such as physical devices, watches, home appliances, vehicles, animals, and even peoples...among others) connected that may provide services via the internet infrastructure (Internet backbone). These connected "things" have been acquired the intelligent feature by integrating them sensors and actuators: to gather information from the environment and to control their own decisions without any human interference [4].

A Applications

The internet of things seeks to improve the quality of life and make it more sophisticated. Hence, this technology has been adopted in various fields. Consequently, a tremendous number of applications have shown up. We can list for examples:

- Smart home: It aims to connect all homes' appliances and physical devices to the Internet network, which provides many applications that make our lives easier [5,6].

- Healthcare: Instead of visiting the doctors periodically, the internet of things uses devices worn by patients, and specialized sensors injected into their bodies to track them and collect information in real-time relating to medical parameters (heartbeat, blood pressure, blood sugar, etc.). The data are transferred to a distant server, which allows the doctors to remotely monitoring patients in serious situations [6].

- Smart industry: Implementing the internet of things in factories is going to revolutionize the manufacturing domain. It will change logistics by offering an effective way of transporting goods [7].

B Architecture

Internet of things technology connects a large and varied number of things through the internet. This explains the need for layered architecture. Researchers have not agreed yet about the unique or standardized architecture of the internet of things. However, the basic model which is typically in use is a three-layer architecture. This architecture [8] consists of the application layer, the network layer, and the perception layer, as depicted in figure 1.

- **Application layer:** The transmitted data via the network layer are received at this layer and are used to provide: (i) appropriate services and operations to the end-users and customers [9]; (ii) data services, such as data storage (backup services), data processing, data analysis, and data mining.

- **Network layer:** It ensures the connectivity of all sensing things and allows them to communicate and share data with other connected smart things [9].

- **Perception layer:** It enables environment monitoring. Thus, it is necessary to identify the physical objects and collect information from them, using the smart systems equipped with smart sensors [4].

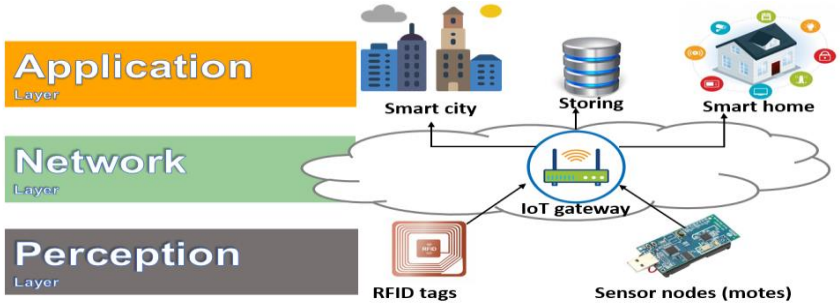

Figure 1: Internet of things basic architecture.

C Enabling technologies

Devices in IoT are equipped with extra capabilities. Therefore, they can act on a large scale and interconnect to the internet, besides providing intelligent services [8]. This paradigm relies on the combination of several technologies that we illustrate in figure 2.

- **Radio frequency identification (RFID):** used for object identification and tracking using radio waves (wireless communication in a short-range). The RFID system is composed of one (or more) reader and several tags that are attached to objects, assigning to each a unique identifier [10]. The function of a tag could be either passive or active. The passive-tag waits for the reader to trigger the communication by sending a query signal transmitted using radio waves. While an active-tag has the power supply that empowers it to initiate communication with the reader [6].

- **Wireless sensor networks (WSN):** A wireless sensor network (WSN) consists of a collection of tiny dispersed sensor nodes, having the responsibility of covering a special geographical area, gather autonomously the sensed information and send it to a warehouse-of-collection called the sink node. Applying WSN techniques in building the IoT technology is going to improve the ability to sense the surrounding environment, and enable the collection, processing, analysis of the sensed data [6,11].

- **Internet Protocol version 6:** Internet Protocol version six (IPv6) offers a highly scalable addressing scheme that covers the scope of a large number of connecting things. Besides assigning unique addresses, IPv6 enables remote control of the devices through the internet [12,13].

- **Middleware:** It is a software layer that allows devices having heterogeneous nature to interoperate [6,14].

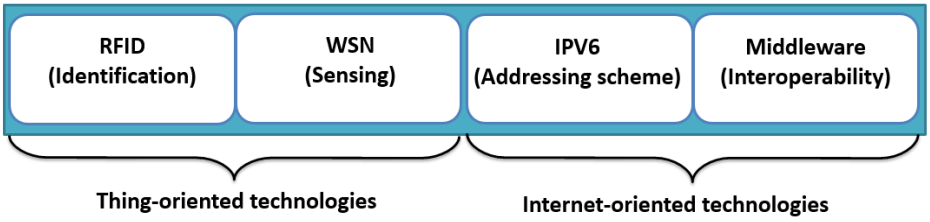

Figure 2: IoT enabled technologies.

3 Routing in Internet of things

Internet of things (IoT) network is composed of a large number of constrained nodes, called motes, with limited: processing power (CPU), memory, and power resources (Battery). These nodes are connected to the internet through a border router. This technology is considered as a class in which both: the router (border router) and its related motes are resource-constrained [15]. These motes will produce a massive volume of data, which requires robust and high-performance routing protocols.

Routing consists of a set of mechanisms implemented by nodes in a network, to find and select an interesting path that optimizes a routing metric, to transfer data between two or more network nodes [16]. In IoT, the network structure class arranges the nodes in a specific structure to create a determined topology for the whole network to perform the routing task. This class uses different routing protocols:

- Flat-based routing: all the network nodes operate in an equally functioning fashion, which means that all nodes are assigned to the same sensing task. Consequently, data redundancy can be occurred, which leads to high-energy consumption [17].

- Hierarchical-based routing: the network is divided into clusters (groups), each one has a cluster head that aggregates the data sent to it by cluster members then forwards them to the border router. This clustering mechanism reduces the number of communication toward the border router and helps to decrease the node's power consumption [18].

- Location-based routing: Routing decisions are based on nodes' location and the distance between neighboring nodes. Nodes location can be determined through a low power GPS (Global Positioning System), equipped on every node. Besides, the distance between neighboring nodes can be detected using the received signal strength. Using nodes location means that not all nodes are working at the same time which is useful in energy-saving [18].

Routing decisions can be affected by network functions due to their versatile applications (Monitoring, tracking, etc.). Accordingly, routing protocols can be classified according to

network operations [19]:

- Multipath-based routing: Is the ability to find an alternative route in case of failure of the main path to reach the destination. This protocol is useful when the application to have a fault tolerance mechanism.

- Query-based routing: It uses querying messages, concerning a specific sensing task, which is propagated in the whole network. The node having matches the data of the query; responds to the node initiating the query.

- Negotiation-based routing: These protocols propose transmitting a series of negotiation messages before transmitting real data, to prevent redundant information to circulate in the network. Negotiation decisions are made based on the availability of the resources.

- Quality of service-based routing: Proposes to make a balance between the two factors: energy consumption and the needed quality of service, as possible as they can, to guarantee an optimized network lifetime.

- Coherent-based routing: Apply two data processing techniques: coherent and non-coherent techniques. In non-coherent routing, nodes process raw data locally before sending it to the other nodes, named aggregators, to perform further processing, because nodes cooperate in the processing task.

A Routing challenges in IoT:

Routing in sensor networks is very challenging due to different characteristics that distinguish them from other networks. An efficient routing protocol should consider these characteristics. The major challenges involved in designing network protocol for IoT are [16]:

- Limited resources: in terms of power supply, processing, memory, and bandwidth.

- Node Deployment: A proper node deployment scheme can reduce problem complexity (communication, routing, energy consumption) especially when the number of nodes becomes bigger. Therefore, nodes deployment is a basic issue to take into consideration when designing any routing protocol.

- Node mobility: Sensors can be attached to moving devices. Thus making the topology of the network frequently changing (dynamic topology issue). Moreover, routing information from or to moving nodes is a challenge. A dynamic phenomenon, on the other hand, very often requires regular sending of information and therefore more data to be sent (which may consume more energy).

- Fault tolerance: Devices in IoT systems are prone to failure (depletion of power supply, communication link error/interference, hardware damages, etc.). The failure of one or a few nodes may degrade the performance of the network. Routing protocols should have mechanisms to handle such unexpected failures, to find alternative paths, and avoid losing data.

- Quality of service (QoS): For some applications, it is necessary to ensure a certain quality of service parameters (such as delay, throughput, jitter, and packet delivery ratio) when delivering data, otherwise, the information becomes unnecessary.

4 Machine learning

Machine learning [20] is an artificial intelligent subfield that is concerned with the design and development of algorithms and techniques that allow computers (any computing devices) to learn by themselves instead of being programmed. From a set of giving examples, machines can learn to extract specific knowledge that is used to recognize hidden patterns. These last are used to make predictions and generate (infer) a fitting behavior in a completely new provided situation (new example). Consequently, applying machine learning methods improve systems' performance over time. Thus, with lots of involvements and experiences, the machines become more matures.

There are three major learning paradigms in ML, based on how the learning process is achieved [20]:

- Supervised learning: The machine is trained using a labeled dataset. The extracted knowledge is used to predict future and unknown instances. Many methods and techniques are used in this category, among the main ones, we can cite:
    1. Decision trees,
    2. Bayesian networks,
    3. Support vector machines,
    4. Neural networks,
    5. Deep learning.

- Unsupervised learning: This is used when the provided dataset is unlabeled and the expected outcomes are unknown. In this learning paradigm, the machine tries to make sense of the data and create models on its own.

- Reinforcement learning: Addresses the problem of how an autonomous agent behaves in an environment to choose an optimal action that maximizes a reward while making a transition from one state to another [21].

5 Literature review

In the literature, many research works have introduced machine-learning techniques in the networking field, to optimize or even solve different routing issues. In this section, we try to recap some of the researches that have used machine-learning techniques to solve various routing issues.

In [22], authors are interested in reducing the energy depletion issue in wireless sensors network (WSN) to guarantee a prolonged network's lifetime. Hierarchical Routing - in which the network is divided into clusters of nodes, having a cluster head at each- protocols are the most used in WSN because of their energy-saving behavior. Consequently, the authors present the hierarchical routing paradigm using the Support Vector Machine (SVM), which is used to solve clustering problems. The idea of their proposed algorithm is to assign the sensor nodes to the nearest cluster while balancing the energy dissipation among the cluster heads. They also try to keep the "minimum distance" between each node and the cluster head as larger as possible. The algorithm iterates until achieving the desired (the optimum) distance: neither too close, to evade creating noise, nor too far to save energy from unnecessary depletion. The authors use Network Simulator 2 (NS-2) to compare their proposed protocol with Low energy Adaptive Clustering Hierarchy (LEACH) protocol based on energy, packet delay ratio, processing overhead, and memory overhead. The simulation has been performed using three scenarios, which are: small, medium, and large scale WSNs. The results show that the proposed algorithm performed better than the LEACH protocol in all of the three tested scenarios and on each of the energy depletion parameters mentioned above.
In [23], the authors were interested in optimizing the forwarding task in VANET (due to the fast-moving speed of the vehicles, this result in rapid changes in the network topology, which can cause instability of links). They list Greedy Perimeter Stateless Routing (GPSR), which is a typical location-based routing protocol as one of the used protocols to solve some of VANET problems. Still, they argue that GPSR has a flaw where it only considers the hop distance while choosing the next-hop neighbor. The selection of the next-hop node as a forwarding node in some cases is not optimal. To address such a flaw, the authors propose a new algorithm namely, Greedy Machine Learning Routing (GMLR) by applying a machine-learning algorithm: Support Vector Machines (SVM), to improve the routing metric model in location-based routing protocols like GPSR. The author's proposed algorithm is divided into two phases. The first phase; the data preprocessing phase: the data are collected by floating cars (data of Beijing), that track the general actions of vehicles (locations, velocity). Therefore, the data packet transmission between vehicles can not be seen. Thus, packet transmission is generated later. These floating car data are gathered in large numbers and set as a mobility file in NS-2. The second phase is the machine-learning phase; here the SVM with a linear kernel function is applied to classify simulation data, where LIBSVM is used as a machine-learning tool of SVM. Two performance metrics are used to examine the superiority of their proposed method: data packet delivery rate and average end-to-end delay. To examine the chosen performance metrics, they change the vehicle moving speed average multiple times. The results show that GLMR can reduce packet loss and network delay compared to GPSR.

In [24], the authors presented a routing scheme based on the reinforcement-learning algorithm that provides an optimal solution (least busy paths) instead of the shortest path solution in the mobile ad hoc networks (dynamically changing node locations). For this purpose, they simulate a network composed of 42 nodes (a grid of 6 * 7 nodes) that move randomly without collision within a rectangular plane using a circular motion boundary. The RL based algorithm works according to the rewards and penalties it gets from the performed steps. The learning process is updated, by each agent (at each node), from each step of its learning outcomes. When a packet is generated, the node seeks to send it to the destination node. If it (destination node) is one of the four nearest neighbors, it sends the packet directly to it, and it updates the reward. Otherwise, it finds the least busy neighbor. When the neighbor node receives the packet, it updates all delays and rewards or penalties after estimating the time of the rest path. This algorithm is iterated until the packet reaches the final destination where the packet is destroyed. The results show that when the packets load getting bigger, the RL based algorithms outperform the shortest path algorithm.

The authors of [25] propose the use of a Q-learning algorithm, which is a reinforcement learning technique, to find the shortest path to a destination node with the optimal capacity of the base stations (eNodeBS/gNodeBs network node) in the 5G self-organizing network (SON). They propose a methodology, called: User Specific-Optimal Capacity Shortest Path (US-OCSP) routing. This methodology works with two primary metrics: the available capacity at network nodes (eNodeBs/ gNodeBs) and the distance. The methodology is implemented as follows. First, they determine the available capacity of all 4G and 5G network nodes that may serve the user.
This is achieved by calculating the Physical Resource Block (PRB) utilization of each eNodeBs/gNodeBs (if the PRB utilization of an eNB is below a "threshold" then it is declared as "available", or it is declared as "busy" in the opposite). After that, they apply the Q-learning algorithm, and it is implemented as follows: the agent should first interact with the network (environment) to explore different paths from source to destination nodes, to achieve at last the optimal path. The movement (Action a) from one network node (State s) to another (State s) results in an immediate reward (r(s,a)). The reward value depends on the couple (valid link, how far or close the node is from the destination). After that, computing Q value for the transition using the Q-learning algorithm, continuing the refinement until reaches nodes that serve the destination. The authors prove the effectiveness of this methodology by a demonstrated scenario using a network simulated in ns-3 followed by the ML implementation in Python. The results showed that the shortest path with optimum node's capacity is rapidly determined which could help network providers to meet the end-user demands by finding the most efficient path and optimizing network resource allocation.

In [26], the authors are interested in the Opportunistic Internet of Things Networks (OppIoT) that were introduced to overcome the limited availability of network infrastructure in IoT applications. Thus extending the geographical area of connection (Intermittent network connectivity and a lack of fixed infrastructure). End-to-end routing paths between the source and destination in OppIoT are non-existent, which makes ensuring a high rate of successful message

delivery an issue to solve. The authors are inspired by previous studies made in Opportunistic Networks (OppNet) “a sub-class of DTNs” that share many similarities with OppIoT Networks, such as the store-carry-forward principle for message transmission (relay nodes store messages in a buffer and opportunistically forward them to other nodes that come in contact with them, to get these messages closer to their destinations). The authors proposed a routing protocol called Cascaded Machine Learning-based routing protocol (CAML). This protocol is built upon MLProph (which is a context-aware algorithm that utilizes ML algorithms for making intelligent routing decisions after observing some features of the nodes) and proposes a cascaded machine learning technique with a two-stage classifier. It consists of a Logistic Regression classifier at the first stage and the same Neural Network employed by MLProph in the second stage, to solve a class imbalance problem that the authors believe that exists in MLProph. The authors simulate and compare their proposed protocol (CAML) with the HBPR, PRoPHET, MLProph, and KNNR protocols using a wide variety of performance metrics (Message Delivery Probability, Average Hop Count, Packets Dropped, Network Overhead Ratio), through the Java-based Opportunistic Network Environment simulator. The results display the superlative performance exhibited by CAML, compared to other ML and non-ML based routing protocols.

To automate the routing decision in Opportunistic IoT networks, the authors of [27] use an unsupervised ML method, called GMM (Gaussian Mixture Model), to propose a novel routing protocol for OppIoT called GMMR. This last is implemented in two phases, training and routing. In the training phase, the network context information is extracted and stored as a matrix of features. The selected features are destination encounter frequency, distance from destination, buffer occupancy of a node, and the number of successful message deliveries. The extracted dataset is used to train the GMM model. This trained classifier is then used in the routing task, to first, create labeled clusters and assign the devices to each cluster. After that, the GMM classifier predicts the cluster label for each: the destination node and the neighboring node. If both of them belonging to the same cluster, then the message is sent to all nodes on the cluster containing the destination node. In this way, the network is protected against flooding messages. The results gained from the simulations showed that the proposed GMMR protocol performs better than PROPHET, MLPROPH, HBPR, and KNNR in terms of average hop count, the number of message drops, delivery probability, and overhead ratio.

The following table 1 summarizes these works:

Paper	Networking field	Routing Problem	Routing protocol	Machine learning algorithm	Network simulator	Evaluation parameter (performance metric)	Obtained Results
[22]	WSN	Efficient routing with optimal energy-saving	LEACH	SVM	NS-2	Energy; packet delay ratio; processing overhead; and memory overhead.	SVM based routing utilize less energy compared to LEACH
[23]	VANET	Optimal next-hop forwarding node	GPSR	SVM	NS-2	Packet delivery rate; network delay.	Reduce packet loss and network delay compared to GPSR
[24]	MANET	Optimal path selection	-	Reinforcement Learning	-	Average delivery time	Near optimal solution
[25]	5G Self-Organizing Network	Shortest path routing with optimal capacity of base station	-	Reinforcement Learning (Q-learning algorithm)	NS-3	Throughput; bit rate	Shortest path + optimal capacity + optimize network resource allocation
[26]	OppIoT	Routing protocol with high rate of successful message delivery	MLProph	Logistic Regression classifier, then Neural Network	ONE simulator	Message delivery probability; average hop count; packets dropped; Network Overhead Ratio	Superlative performance compared to MLProph
[27]	OppIoT	Automate routing decisions	Context-aware routing protocols	Gaussian Mixture Model	ONE simulator	Average hop count; overhead ratio; delivery probability; number of dropped messages	GMMR performs better than PROPHET, MLPROPH, HBPR

Table 1: Summary of main research works using machine learning in routing.

6 Conclusion

In this paper, we present some existing solutions using machine learning techniques to improve routing protocols in the internet of things networks. Most proposed solutions start by collecting data from nodes and then pre-process it to build a dataset to use in the training phase. In the training phase, a decision model is built using a machine learning technique such as Nearest neighbors, support vector machine, decision trees, Bayesian network, and neural network. Our future work is to propose a framework to learn from the historical routing data of each node to build its model to use in routing operations in mobile networks. In this framework, each node sends its routing decisions to a specific server at each routing operation performed using a traditional routing protocol. The sent data contains the taken decision (next hop) and its properties such as time and date, original node, destination node, previous node, etc. After a sufficient period, the server uses gathered data to build a decision model for each node that allows taking an important number of routing decisions without the need to use a traditional routing protocol. We think that such a framework will reduce resources used with routing protocols and can even avoid their use altogether.

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