Determination of Suitable Resource Discovery Tool and Methodology for High-Volume Internet of Things (IoT)

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Abstract. This paper discusses several issues supporting a knowledge-based methodology for discovery of high-volume IoT resources in the simulator NS-3 environment. We found the concept was developed in previous researches, especially based on widely accepted concepts of Q-Learning discovery model. The model is validated using samples from emulations of tested data in the NS-3 simulator. Proper simulation in NS-3 based on the different modules such as checkpoint and restore was used to model and analyse the data. The main feasibility checkpointing concept of simulations in the NS-3 processes were using Distributed Multi-Threaded Checkpointing (DMTCP) to run on a single machine and Message Passing Interface (MPI) under distributed machine to speed up the NS-3 model initialization and execution. As the chosen model to be implemented in this analysis, the Q-learning algorithm proposal offers a possible solution for addressing evolving IoT environments and configurations. Q-learning is one of the successful techniques available for the exploration of IoT nodes, but context-based problems have already been established and simplified as issues of dedicated server management, IoT object data acquisition issues, and unique application requirements. The findings empirically support the validation of the Q-Learning model improvement for high-volume IoT resource discovery cases. The study will contribute to the new model development by providing new insights on the conceptualization and validation of knowledge-based methodology based on widely accepted techniques and approaches.

1. Introduction
The IoT allows manufacturing, public and private sector organisations to improve the productivity of operations. New IoT technologies are now being rapidly implemented by academies and industries. Several concepts for innovation have already arisen, including LoRaWan, narrow-band IoT (NB-IoT) and HaLow Wi-Fi [2]. However this rapid growth increase has led to delay, privacy and new IoT problems, such as how to integrate millions of IoT devices from different suppliers using specialised application applications [3].

Other continued efforts in IoT interoperability will cause in widely used standards in the future. For now, we do not know the outlook of the standard, but for the purpose of further discussion in the
study, we developed interoperability models that include IoT entity integration, discovery and semantic interoperability and address the list of IoT scalability capabilities [1].

IoT, due to the advancement of communication technologies, is the fastest growing technology around us. In all settings, IoT platforms have different capacities and capabilities. There are many types of IoT platforms, resource discovery techniques and simulators in the literature. Choosing the best IoT platform is the most complicated process up to this point and many are still discussing it. This challenge involves how millions of IoT devices can be communicated from various manufacturers and how thousands of new IoT devices can be incorporated into the existing network infrastructure. The discovery of high-volume IoT tools adds another layer of challenges to the selection, discovery, access and review of online data from various platforms. Although other knowledge is constantly written, the selection of NS-3 as the right software has been proven based on our previous clear literature [20]. Therefore, determination of the best identification method is an appropriate step in solving this problem.

2. Issues In IoT

The IoT technology that emerged today has mastered in the various fields needed by consumers including medicine, education, transportation, manufacturing, sports et cetera. Through using their own method of data transfer, IoT systems are now coming into the market. Each of these technologies for communication and information does have its own special and interesting benefits.

It is possible to reduce IoT challenges into three distinct circumstances. First, the deployment of IoT devices from various manufacturers, each of which uses different specialised applications; second, the deployment of new IoT devices into the current network infrastructure; and third, the configuration of new IoT devices with different levels of protection. The rapid IoT development has, however, introduced various opportunities, including platform selection options, methodology accuracy in the resource discovery, and selection of simulators for verification purposes.

2.1. IoT Simulator

Simulator selection was developed to react to the IoT networks, which aims to provide end-to-end support for all IoT components, based on simulator classes that are appropriate for networking and IoT simulation, among others. In order to facilitate the necessary IoT implementation, it also focuses on the elements of broad IoT applications for data processing and then continues to grow. Various network communication systems can provide IIoT with many choices for customising existing technologies with their features. In IoT study, many network simulators have been used, but only three types of simulators can be used intensively on the basis of the context and scale of architectural layer coverage. [39]. We will find some of the simulators shortlisted in 2019 and above that have been updated and published. Several similar instruments with diverse and different histories have been used to evaluate the feasibility of the simulator, and to prevent functionality problems in the future. They are OMNet++ [8], Qualnet [9], iFogSim [10], IoTSim [11], and NS-3 [12] which need to be carefully studied.

2.2. IoT Platform

Selecting a suitable IoT platform for a given area of application is a challenging task while choosing from the mess of numerous huge IoT platforms. [1]. In order to support IoT using embedded machine learning and sensors, LoRa contact has now gained a lot of interest and collaboration from academics and industries [4, 5]. It has been proven that LoRa is the most appropriate platform to support IoT applications nowadays. As one of the variables suggested by previous researchers, we look forward to LoRa as the best choice to help IIoT [13, 14].

2.3. IoT Resources Discovery Model

Resource discovery can be defined as a systematic method of identifying and accessing specific sources to obtain the requested information to analyse it. The accessing activity is based on the
requested query to get specific data such as for identification sources, patterns, and events. Here we look forward to the usage of collaborative services to obtain data from different sources for analysis and eventually to deliver excellent results. For control purpose, a time period in data collection for disaster monitoring could be limited to the discovery of resources [18]. However, if special methods or extra components are not used to fix them, not all resource discovery approaches are appropriate. The Breadth-First Search Technique (BFS), for instance, is the earliest source discovery mechanism derived from mathematical formulation models and is still used in many unstructured P2P networking areas for resource discovery [19]. According to [19] it was noticed that BFS was able to increase the combined efficiency rate through the implementation of alpha multipliers. This demonstrates that if any appropriate element is applied to the discovery processes, the output can be improved for most discovery methods.

Data scanning in the new IIoT shows that are only 2 popular techniques, Context-Aware Resource Discovery and Context-Based Search Techniques. Context-Aware Resource Discovery under Learning Based Approach offer Q-learning as intended by [22] Works by evaluating an action-value attribute based on controller experiences with the framework [21]. Q-learning is a modern paradigm for node exploration using Context-Aware Resource Discovery.

3. Recommended Solutions

According to the results by several researchers in the related field, some of them recommend that specific solution should be used in specific issues. The latest papers showed the solution from different angles but we need to review all of the references and other relevant materials, so we can divide them into several solutions.

Based on the limitations noticed by the researcher, there are few ways to improve the study in future time. For example, in order to make the study to be more representative, it is recommended to use a bigger sample size with suitable simulation tool and resource discovery model. However, all of these improvements will have to be evaluated continuously.

3.1. IoT Simulator

NS-3 is a licenced free software simulator proposed for experimental and academic use and encourage for discrete network simulation cases [23]. The deep learning methods of the NS-3 programme are very valuable to use as an actual simulation environment, due to its real-world interconnectivity and the implementation of several real-world protocols. With the facilitation of certain use cases for communicating with real systems, NS-3 can also help IP and non-IP related research and look more plausible.

Until recently, NS-3 was one of the preferable simulators used for this purpose. Publicly a new version of NS-3, has been released and is undergoing active development. The latest version, NS-3.30, was released with various platforms and protocols implemented. We can find several research implementation using NS-3 such as Wi-Fi Halow, NB-IoT, LoraWAN, QUIC, Protocol, Queuing (AQM), and TCP [2, 23].

Several devices are linked within every large-scale organisation or project through advanced wireless technology for various applications such as communication, surveillance, national defense, message, social media, or even domestic security. Due to its ability to support large IoT or high-volume IoT, the advent of IoT is especially helpful for high-tech wireless devices. Different paradigms including IIoT, edge computing, cloud computing and fog computing are responsible for these high-volume IoT distributions. All of this propagation, requiring an efficient and high-performance network ecosystem and active communication, has opened up a field of simulation science.

We are looking forward to all the NS-3 simulator's great potential because it has greater reputation. NS-3 is based on an previous version, NS-2, and it can be used to simulate the IoT perception layer by generating WSN simulations. For related protocols, OMNeT++ has the same capacity and similar characteristics, but NS-3 will minimise application-level protocol support to make it simpler. NS-3 is a
commercial software that can also be used extensively in educational, research and IoT analysis as an open source tool.

3.2. IoT Platform

LoRa stands for long range that used a spread spectrum modulation technology. It has interesting characteristics, such as greater distances, low energy consumption and stable data transmission, to support IoT applications. LoRa is able to fill the gap between mobility and low power due to its ability to support long communication ranges, particularly for high volume IoT [24]. To support the selection of LoRa as a forum for massive network IoT, several parameters are listed here. The selected parameters were classified by the LoRa researchers based on the required implementations.

Table 1: LoRa output with distinct parameters.

| No  | LoRa Parameter | Implementation Result |
|-----|----------------|-----------------------|
| 1   | Security [15]  | Proposing a new LoRa structure for the current version of LoRa, LoRa version 1.1 is able to resolve many of the security concerns previously mentioned, including the implementation of LoRa's key features, as well as seeing possible risks to the security of the protocol and offering a solution to the security threats involved. |
| 2   | Operation [16] | Building of a new LoRa activity with different Spreading Factors using chirp spread spectrum. This contributes to improved delivery rates with increasing service rates but shorter delivery times. |
| 3   | New Idea [17]  | Come up with new ideas to propose a new LoRa module in the most appropriate simulator of NS-3 and at the same time, new protocols and the effects of various parameters on the network can be studied. |
| 4   | Reliability [15] | Increase reliability by partitioning the collision state and framing frame, partitioning the all packet based on the LoRa frame format. The result indicates that even after the collision, as long as the last six symbols of the preamble and the title do not overlap, the frame continues to exist. |
| 5   | Scalability [14][15] | LoRa scalability measurement to keep all nodes running at around the same period. For a real sensing environment, a study of scalability for LPWA technology has been performed. The method of using LoRa sensors to explore the detection of this behaviour. |
| 6   | Frame Collision [14] | Continue investigating LoRa frame impacts in different environments with Packet Delivery Ratio (PDR) and perform frame collision assessments. The results indicate an increased PDR in the scenario of a single gateway. A closer gateway led to the higher PDR levels. |
| 7   | Physical Layer [16] | Analyzing the physical layer output of LoRa in many cases of IoT use. LoRa has many benefits, such as long range, resilience to multipaths, low energy consumption, correction of forward errors, robustness, and so on. In LoRa, the physical layer metrics determined are different, including bandwidth, transmission capacity, code rate, etc. |
| 8   | Performance [13] | LoRa performance monitoring with 5 parameters, and all calculated parameters are important. If one of them changes, then it changes the other parameters. The effect will decrease the size of the package in an indoor experiment, thus decreasing the amount of re-deliveries and packages dropped. The findings suggest that contact can be accomplished without issues and that packet drop in outdoor experiments is small. |

3.3. IoT Resources Discovery Method
Discovery of resources will require the use of detailed knowledge. Data may be words in a document, table information, images, files, or measurement packets sent by a computer. Data development can be categorised as linear and exponential, but a more drastic increase is exponential. After it has been obtained, prepared, analysed, and displayed in a functional way, data can no longer be kept on a few machines or processed with only one tool and transformed from its raw format into information. Data that is so big, fast, or complex that it is difficult to store, process, and analyse using conventional applications for data storage and analytics.

Basically in data analysis, data typically involves cleaning, transforming, and manipulating. Besides that, there are three main activities on IoT data search, including optimization using indexing, discovery, and ranking solutions. [27]. In related to resource discovery, this refers to the process of automatically or manually crawling, locating, and allowing resources to be found in IoT environments. Indexing means sorting the IoT data, including retrieving and searching for the data, to allow for easy access to their resources. Discovery involves searching, finding and exploring data tools based on the main key search attributes that can provide the response to the question requested. Ranking means prioritising IoT resources on the basis of many functional or non-functional parameters. The focus of our research here is narrow and limited to the exploration of IoT resources.

In the meantime, [22] in the field of resource management, resource discovery within the mobile IoT network can be categorised as Time Synchronized Protocols Approach, Deterministic Approach, Colocation-based Approaches, Fully Distributed Opportunistic Approach, and Context-Aware Resource Discovery Approach in various situations.

Today's IoT and IIoT technologies can be grouped into Society, Industry and Environment domains [25]. Refer to idea of [26], every searching techniques in any IoT areas, such as event-based search, location-based search, time-related search, content-based search, spatiotemporal search, context-based search, real-time search, and user-interactive search, are varied and not similar to each other. In short, we can conclude the searching systems only can work on the basis of Text-Based Approach, Metadata-Based Approach, and Ontology-Based Approach classifications.

4. Features of Resource Discovery Methodologies
The media is also numerical data in the modern age. It is defined as digital data by ones and zeros. IoT data is obtained from wired or wireless networks of smart things such as computers, sensors, and utilities as well as data use in the other sector. IoT data, however, can require more sophisticated analytical tools for different data types, and it is also streamed in real time or almost real time, in greater quantities and in different formats [31]. So, the IoT data from the linked objects is then created as data streams because the structured or unstructured IoT data must be organised in real-time basis.

There are various methods that allow resource discovering with their unique features and in different parameters. It can be presumed that multiple parameters such as efficiency, latency, bandwidth, responsiveness, security, speed, robustness, usability, reliability, power consumption, functionality, energy consumption, data integration, and so on can be calculated and tackled by almost all methods. In short, to explain their performance for potential use, the methods addressed in the field of IoT resource exploration have been refined. In table 2 below, we have listed only the related knowledge-based learning methods and compared their key advantages and disadvantages as a reference for potential researchers.

| No | IoT Discovery Method                                | Main Features                                                                 |
|----|-----------------------------------------------------|-------------------------------------------------------------------------------|
| 1  | Context-Aware Resource Discovery [22]               | Effective learning of higher and lower duty cycles. Learning is accessible on static, not mobile nodes. |
| 2  | Efficient Application-layer Discovery Protocol [22] | Fast rate of discovery but more time spent ads on node.                       |
| 3  | Adaptive Probabilistic                              | Over time, searching capabilities increase. Nodes are randomly                 |
Search [25] and equally likely to be chosen.

If no suggested node is identified, the artificial intelligence procedure using queries is forwarded spontaneously.

Learning Automata-based Resource Discovery [25] can simplify the network flooding issue, but still have fault-positive error problems.

Improved Adaptive Probabilistic Search [25] better performance than traditional random walk / query and APS; and its dependence on ant-colony optimization features.

Discovery of Heterogeneous Multiple Compute Resources Framework [25] responds to complex demands, but with low robustness and protection.

Content-Based Search [22] is not feasible to give access to current and previous data and detailed search results with limitations on high-level results, but it have effective regulation of IoT object management, although it is difficult to obtain context-information data.

Location-Based Search [27] takes more time and needs massive storage space in combination with query routing techniques.

Social Structure-based Search [27] with more consumer activity and human-made benefits, but restricted to traffic congestion and scalability problems.

Semantic and Ontology-based Search [27] effects can be modelled in natural language, so the integration of middleware for management needs.

Resource and Service discovery [27] support QoS parameter, so that additional subscription management is needed.

4.1. Knowledge-Based Methodology in IoT

The involvement of IoT applications is for the use of million types of devices. These devices are used in a variety of ways either statistically or independently. The movement of the IoT scenario will always occur encompassing both static and dynamic nodes. This case provides an incentive for nodes to connect with each other, in turn requiring a resource discovery or searching process. There are various scenarios commonly used for this search ranging from basic to advance.

![Figure 1: Basic Searching Structure](image_url)
opportunities do the heterogeneous static and dynamic devices touch one another. This communication opportunity is used by the machines to relay data from the source to sink when no direct connection is available. In situations such as smart cities, where predefined end-to-end paths are not available, such opportunistic networking is helpful.

The Q-learning Searching Structure is defined in Fig. 2 by learning an action-value function based on an agent or operator's experiences with the system and the immediate reward it generates [28]. An agent's goal is to find the action that maximises its long-term reward by testing out all the potential actions while being in a given state.

4.1.1. Learning Process. The algorithm operates an ideal mobile and static node strategy for performing maximum and minimum latency behaviour based on mobility patterns of contacts. High reliability and network connectivity behaviour allow contacts to be discovered within a shorter and longer latency duration time, respectively, but with different energy costs. During Q-Learning, various activities are attempted with the goal of learning the sequence of actions that optimise the reward, which will be set within the sub-action period and independently of the energy depending on the receipt of the beacon. Contacts occur at various times over time, but if they have a similar process that regenerates itself the Q-Learning algorithm can learn this behaviour and try to approach the best action, each time subject to the reward [28].

4.1.2. Experimental Phase. The system enters the experimental process after the completion of the learning stage. The system is evaluated with real world data at this point, and only optimal results are obtained. The system will use and expand machine learning approaches. It can be used to measure the discovery latency reducing in parallel.

4.2. Self-Measurement the Knowledge-Based Method

Based on the capabilities of NS-3 simulator, it involvement in emulation greatly impacted the in-depth study in field of network usage today. The large scale and high-volume IoT doesn't help any of them. We have outlined the simulation parameters in Table 3 before digging into the outcomes. We used the same parameters in the simulation of each of the three scenarios. To assess network efficiency, two metrics are used; first, the number of packets received to find the total network throughput. Second, the rate of packet error depending on the distance to the gateway for reliability measurements. To verify the efficiency of our proposed techniques, we have run simulations in different volume of data and number of nodes in 9 different scenarios:
Scenario 1: a network with 100 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 128 bits packet size.

Scenario 2: a network with 100 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 512 bits packet size.

Scenario 3: a network with 100 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 1024 bits packet size.

Scenario 4: a network with 250 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 128 bits packet size.

Scenario 5: a network with 250 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 512 bits packet size.

Scenario 6: a network with 250 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 1024 bits packet size.

Scenario 7: a network with 500 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 128 bits packet size.

Scenario 8: a network with 500 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 512 bits packet size.

Scenario 9: a network with 500 nodes and spread data in a hybrid topology and has a central gateway in the free space propagation. The gateway responds within every 100 messages and has spreading factors with 1024 bits packet size.

Table 3: Parameters of Simulation

| Parameter            | Value Set                      |
|----------------------|--------------------------------|
| Simulator Type       | NS-3 version 3.30              |
| Simulation Time      | 30 sc                          |
| Number of Nodes      | 100, 250, 500                  |
| Topology             | Hybrid (grid) topology         |
| Transmission Rate    | 2 pkt/sc                       |
| Transmission Range   | 100 m                          |
| Packet Size          | 128 bits, 512 bits, 1024 bits  |
| Hello Rate           | 1 pkt/sc                       |
| MAC Layer            | 802.11 DCF                     |
| Propagation Model    | Free Space Propagation         |

4.2.1. Measures. The measurements demonstrate that it is possible to model tiny networks pretty quickly, except that identification requires a lot of effort. The specifications increase dramatically for the latter scenario. This is because of the network retransmissions and approvals. High-volume networks need more bandwidth to archive same level of output, but adjustment in the number of nodes will affect their sum of bandwidth directly.

4.2.2. Data Collection. The data for this experiment are collected using a set of random data (100, 250 and 500 nodes) in different packet sizes (128, 512, 1024 bits).
4.2.3. Optimization. In order to enhance the discovery of point nodes in the IoT network, the knowledge-based approach known as the Q-Learning model must be conducted using several components such as the user agent, service agent and reply agent. An agent's goal is to find an action that maximises its long-term reward by attempting all possible actions while in a given state. [27]. Simulation speed can be done in several different ways, with solutions that differ from the use of programming techniques and languages that result in faster executable code, parallel programming techniques such as Message Passing Interface (MPI), to massively parallel computation using High-Volume IoT discovery, to take advantage of high performance computing assets. The widely used OFED API for InfiniBand and its integration with various MPI implementations and resource managers are provided by DMTCP. [28]. There are three particular areas where DMTCP can support your parallel computing needs: i) Parallel Languages: Transparent support for parallel languages MPI, Unified Parallel C/C++ (UPC), etc. These are viewed by DMTCP as just a "black box" consisting of distributed processes; DMTCP also supports transparent checkpointing of the ssh connections often used by these languages, ii) The Network: Transparent support for distributed processes over TCP sockets and over InfiniBand, iii) Resource Managers (the batch queue): Support for Checkpoint- Restart for several popular resource managers (e.g., SLURM, Torque).

4.3 Result and Analysis

Implementing this analysis with a model-free Q-learning algorithm to dynamically estimate optimum controller settings without any system knowledge for linear systems. This selected Q-learning algorithm is a possible solution to solve the current IoT's evolving environments and settings. Q-learning is one of the successful methods shown to be available for the discovery of IoT nodes. Context-based issues have already been established and simplified in terms of dedicated server management, IoT object data acquisition problems, and basic application requirements. As seen in Table 2 above, there are still some apparent drawbacks, so there are still important reasons for researching the implementation of this new methodology to allow for in-depth analysis in the future. With support from MPI, the discovery process will increase in output, but decrease in processing times.

4.4 Discussion

Resource discovery using checkpoint would clearly have some role for the total memory footprint of the simulation, including all processes to support the model of Q-Learning. In order to provide an indication of how long checkpointing takes and how checkpoint sizes tend to increase with time during simulation execution to provide an indicator of how large each checkpoint is going to be, we have studied using a few instances of simulations bundled with NS-3 based on the outcome. This approach can provide pace by minimising repetitive calculations and generating similar results under the correct conditions and with the appropriate choice of checkpoint time.

5. Conclusion

Q-learning in the future IoT environment is the biggest resource exploration in the ubiquitous network. It is the preferred method of exploration to take on several large-scale network powered portable IoT devices. In a LoRa network, the transmitter sends data packets according to the same uplink path, so by optimising the uplink efficiency we can reduce the transmission delay. We checked the selected papers in this paper and then selected the best simulator to verify the discovery of IoT resources in the LoRa network. Using many experiments, NS-3 can yield better output topologies as a simulation tool.

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