(POSTER) Towards Data Dissemination Policy Prediction for Constrained Environments Using Analytics

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***Abstract*—In Cyber-Physical Systems (CPS) such as Wireless Sensors Networks (WSN), disseminating data is crucial. Under energy constraints with limited communications capabilities, performing data dissemination is challenging. In such contexts, common data dissemination methods cannot be used. Nodes must rely on device-to-device communications policies to mitigate the impact of communications on the nodes energy consumption. However, depending on nodes configuration (up-times duration, wireless technology capabilities and energy consumption), choosing a suitable communication policy is challenging.**

This work exposes the problem statement for using analytic algorithms to predict the most suitable device-to-device communication policy, for a given node configuration, to match a given coverage and energy consumption target in a constrained environment.

***Index Terms*—analytics, classification, data dissemination, energy constraint, distributed systems, CPS, IoT, WSN**

I. INTRODUCTION

The use of distributed systems for environmental monitoring is crucial for various applications. It allows to record the evolution of several phenomenons such as air and water quality or earthquake detection over large areas [1]. Several tasks must be performed by these distributed systems such as sensing, processing and disseminating data. They can be built with technologies from the Internet of Things (IoT), Wireless Sensor Networks (WSN) and more generally Cyber-Physical System (CPS). Depending on the deployment context, performing environmental monitoring can be challenging.

The Arctic Tundra (AT) is a particularly harsh environment to monitor, with large isolated areas, where (i) nodes are expected to operate for several months, under a very limited energy budget; (ii) mobile networks provide little to no coverage on the monitored area, forcing nodes to rely on their own wireless technologies; (iii) nodes are not consistently reachable because of harsh weather conditions (heavy snow, rain, humidity etc.). Consequently, monitoring and disseminating data in this context is difficult to achieve.

The Distributed Arctic Observatory (DAO) project is working on overcoming the challenges encountered in this context [2]–[4]. In [5], different loosely-coupled communication policies are proposed. This related work studies four communication policies that can be used in the AT context. Two metrics are considered: 1) the energy consumption 2) the coverage (representing the number of nodes that received the data). The work highlights that, in a given context, a policy can be better than another. Also, depending on the use case, full coverage is not always required, especially in scenarios with energy consumption constraints. A trade off between coverage and energy consumption must be found. However, according to the node configuration (up-times duration, wireless technology and energy consumption), this trade-off can change.

In this paper, a problem statement for using supervised learning classification algorithms to predict the most suitable device-to-device communication policy [6] is proposed. This work shows that the node configuration must be taken into account as it has a significant impact on the policies performance and the nodes energy consumption. In addition, since the DAO context is a highly constrained environment, the prediction models must handle a dissemination coverage target and energy consumption budget.

This paper is organized as follow. Section II presents the context of the work. Section III details the proposed approach. Finally, Section IV concludes this paper.

II. CONTEXT: OBSERVING THE ARCTIC TUNDRA

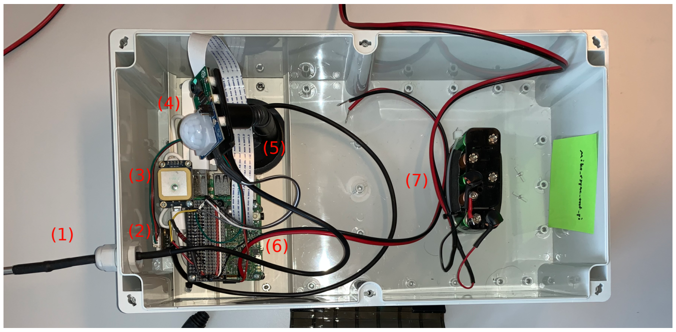


Fig. 1: Early prototype of a Raspberry Pi based Observation Node (ON) [5].

The DAO project proposes to use a distributed system as a monitoring infrastructure for the AT. The deployed nodes called Observation Nodes (ON) can be based on a Single-Board Computers (SBC), allowing for more resources and better programming support, compared to micro-controller based ON. Figure 1 depicts the basic blocks of a DAO ON. This early prototype contains a Raspberry Pi board and

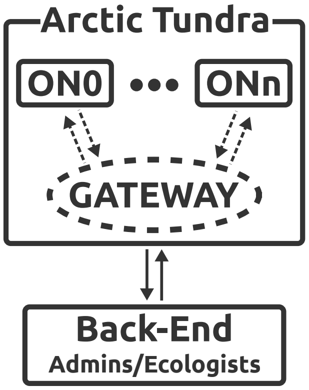


Fig. 2: Overview of the observation system architecture. The “Back-end” hosts a set of services, like [5]. Its connectivity to Observation Nodes (ON) deployed in the Arctic Tundra uses the gateway when available. This wireless gateway is used for 1 to 1 communications between ONs, forming a star topology.

Sleepy Pi micro-controller (6). The embedded sensors include an optical and proximity cameras (5), an inside (2) and outside (1) temperature and humidity sensor, and a GPS (3). From the SBC, several network technologies are available: WiFi, Bluetooth, 4G LTE, LTE Cat M1 and a 4G stick (4). ONs are built with internal and external batteries connectivity (7).

In related work [6], a distributed monitoring infrastructure for constrained scenarios such as the DAO is proposed. This architecture is depicted on Figure 2. The ONs are in charge of monitoring the environment and communicate with other ONs and the back-end, through a gateway (when available). Since the AT is a wide and isolated environment with harsh weather conditions, ONs are expected to operate for a long period of time. Thus, ONs are turned off most of the time and wake up for a short duration, called *up-time*. During this up-time, ONs sense their environment and make communication attempts to other ON to disseminate data.

The ON communicates using one of the available policies (depicted on Figure 3): *Baseline*, *Hint*, *Extended* or *Hint+Extended*:

Baseline – ONs wake up at a random time, each hour, to perform its up-time. When an overlap between the sender and the receiver up-time happens, the sender starts transmitting data. If one of the ONs up-time ends, ongoing communications are aborted and the ON turns off.

Extended – Compared to *Baseline*, the *Extended* policy does not abort ongoing communications and ONs keep communicating until data is transmitted. It implies that up-time duration of ONs can be extended.

Hint – The *Hint* policy is based on *Baseline*. The sender performs additional communications to send a timestamp to receivers. It informs the receivers about the sender’s next up-time, to increase the likelihood of up-time overlaps between them. This timestamp can be gossiped between receivers.

Hint+Extended – This policy combines the principles of the *Extended* and *Hint* policies, with the aim of combining the effects of both.

TABLE I: Simulation Parameters

Parameters		Value	Citations
Bandwidth (Ltnc)	LoRa	50kbps (0s)	[7], [8]
	NbIoT	200kbps (0s)	[7]
Energy states	P_{idle}	0.4W	[9]
	LoRa	0.16W or 32mA at 5V	[10]
	NbIoT	0.65W or 130mA at 5V	[10]
Up-time	Long	3 min/hour	
	Short	1 min/hour	
Data size		1MB	
# Receivers		12	

Simulations were performed in [6], to study the impact of these policies on the amount of ON that are able to receive the transmitted data and their energy consumption. The parameters used for the simulations are shown on Table I. Each run simulates 24 hours of deployment for 13 ONs. Each ON wakes up at a random time, each hour, for a short up-time (1 min) or long up-time (3 mins). In each run, one sender ON tries to transmit data during its up-times to twelve receivers ONs. The simulations assume that ONs use Low Power Wide Area Network (LPWAN) wireless technologies (LoRa or NbIoT) for long-range communication with low energy consumption.

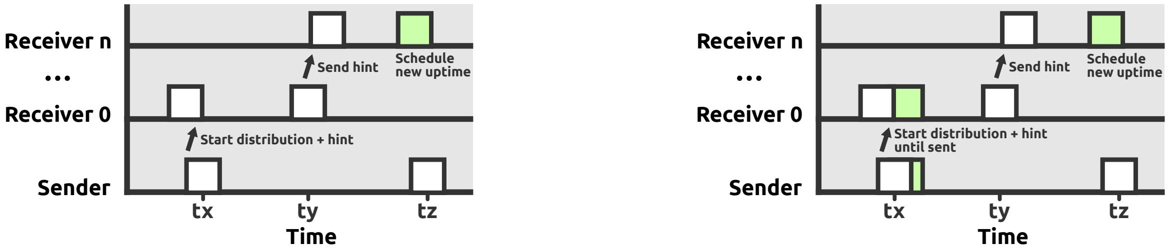
III. APPROACH

The simulation results from [6] show that, each policy has a different impact on the coverage and the energy consumption of nodes. This impact is mainly driven by the nodes configurations. Four nodes configurations are considered. They comprise a wireless technology and the node up-time duration: ① LoRa with $60s$ up-time duration ② LoRa with $180s$ up-time duration ③ NbIoT with $60s$ up-time duration ④ NbIoT with $180s$ up-time duration. The Figure 4 summarises the simulation results obtained in [6] for each node configuration. This figure shows the energy consumption and the dissemination coverage for each combination of policy, wireless technology and up-time duration. The figure highlights the variability of the results according to the node configuration.

As an example, the *Baseline* and the *Hint* policies are not able to disseminate data in the scenario with $60s$ up-time using LoRa. In other scenarios, these policies are able to achieve significant coverage, up to 12 receivers. In addition, the trends of each policy changes with the nodes configuration. Such trends suggest that a supervised learning classification model can be used to predict the correct policy to use in order to save energy and achieve coverage. Moreover, deployment specific budgets, such as the energy consumed and the targeted coverage must be taken into account.

When the scenario requires to meet a certain energy consumption budget for a given coverage, a policy could answer one constraint while violating the other. Hence, a model that predicts the appropriate policy to use for a given coverage and energy budget must be introduced. This work hints at the need to study the feasibility of such predictions using classification models.

(a) Baseline (b) Extended



(c) Hints (d) Hint and extended

Fig. 3: Example of communication scenarios for each policy. Messages, up-times and added up-times are represented as arrows, gray and green rectangles, respectively.

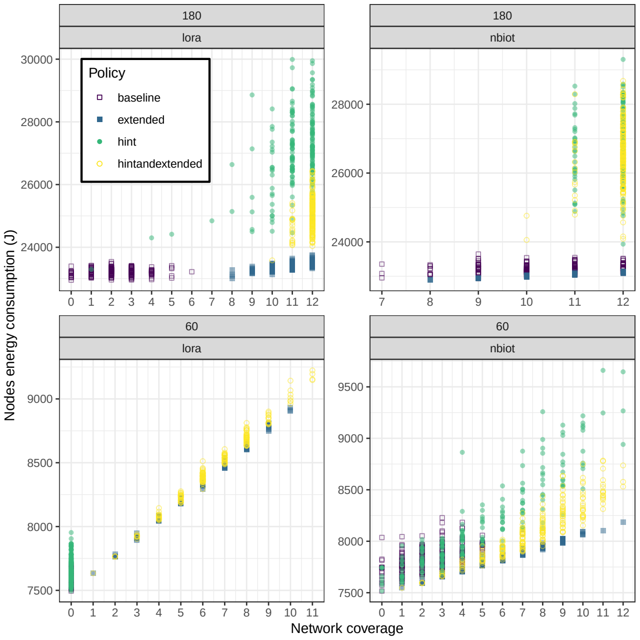


Fig. 4: Summarized results from [6], showing the overall energy consumption of nodes according to the coverage achieve by the communication policy.

IV. Conclusion

Disseminating data in a resource constrained environment such as the Arctic Tundra is challenging. As nodes are limited in energy consumption and network communications, they are not expected to be reachable most of the time. Hence, existing data dissemination techniques cannot be used in such context. Related work [6] propose several loosely coupled data dissemination policy to tackle this issue. However, choosing the correct policy to use is not trivial as it depends on the node configuration, the targeted coverage and the energy consumption budget. This work exposes the challenges and proposes, as a future work, to use classification algorithms to solve this problem.

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