RIS-IoT: Towards Resilient, Interoperable, Scalable IoT

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ABSTRACT

With the introduction of ultra-low-power machine learning (TinyML), IoT devices are becoming smarter as they are driven by ML models. However, any loss of communication at the device level can lead to a failure of the entire IoT system or misleading information transmission. Since there exist numerous heterogeneous devices within an IoT system, it is not feasible to centrally monitor all devices or explore system logs to determine communication loss.

In this work, to maintain the highest possible communication quality and enable devices adapt according to context changes, we implement a lightweight ML-based adaptive strategy (ASB) and deploy it using a memory-optimized approach over the designed Pycom FiPy based multi-protocol IoT hardware. In real-world experiments, ASB equipped FiPy board accurately predicted the RSSI of WiFi 4 & WiFi 5 in real-time and switched between protocols - demonstrating interoperability amongst multiple IoT communication protocols and resilience against communication breakdown.

KEYWORDS

Multiprotocol Switching, RSS Prediction, Edge Intelligence.

1 INTRODUCTION

In IoT systems, the response time of edge devices is calculated during the design phase. These edge devices continuously provide data streams to ensure the smooth execution of a real-time IoT system [1, 2]. However, edge devices are prone to errors and often suffer from communication breakdowns [3] when trying to maintain an acceptable level of communication quality in the presence of external interference - can lead to a failure of the entire system.

In the majority of cases, communication breakdowns occur due to *lack of interoperable mechanism and protocols*. A typical example scenario could be when the warning raised by smoke monitoring edge sensors is not real-time due to a loss in communication quality and without other forms of communication to indicate waning could lead to compromising the safety and health of the workers. The next challenge is the *lack of resilience* where an IoT system is unaware of how to handle uncertainties as it cannot predict failures and automatically switch to alternative protocols.

Another challenge is the *lack of scalability* when non-stationary devices are unable to contribute data. In many use-cases, edge devices stream the operational behavior data of appliances, vehicles, machines, etc., to on-premise or cloud-based servers for historical storage and analytics. The quality of received data depends on the behavior of wireless protocols, which can vastly fluctuate due to signal impairment problems. When noisy data is recorded due to poor or unstable transmission signal quality, during data cleaning, the rows with missing values often get removed even if they were to contain crucial information - reducing IoT device-based data collection scalability.

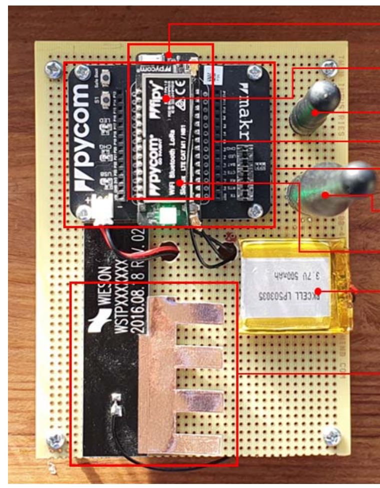

Figure 1: Multi-protocol (WiFi, Bluetooth, LoRa, Sigfox, dual LTE-M) IoT hardware designed, used for RIS-IoT evaluation.

Similar to the above scenarios, there are several cases where there is a need to equip multiple communication protocols on a single device and equip them with algorithms to instruct the devices when to seamlessly switch to improve communication quality [4]. The contributions of RIS-IoT applied research work are: (i) Introducing resilience property in the IoT architecture at the device level to realize reliable information distribution; (ii) Equipping embedded devices with multiple communication protocols and providing interoperability at scale; (iii) Providing run-time re-configuration of devices in accordance with the dynamic-network context.

2 APPROACH FOR RIS-IOT

This section presents our Adaptive Strategy Block (ASB) to improve the resiliency, interoperability, scalability of IoT systems. We next present the design flow and experiments to port ML algorithms like ASB and efficient execution on IoT devices.

2.1 Adaptive Strategy Block (ASB)

ASB is a resource-friendly intelligence layer designed using a radial basis function (RBF) kernel-based support vector regression (SVR) [3]. ASB can predict upcoming issues due to potential degradation

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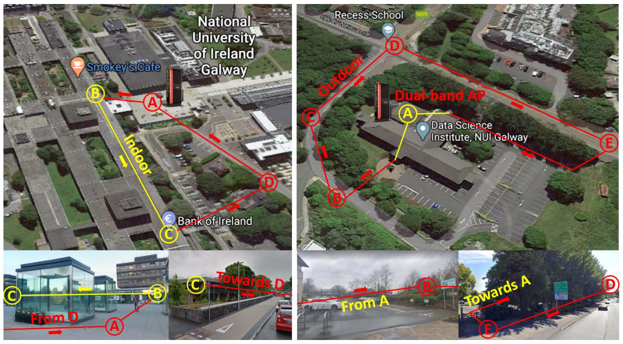

Figure 2: Indoor (yellow trace) & outdoor (red trace) combined experiment sites. Left: Corridor, roads near NUIG. Right: Car park, public roads surrounding our DSI lab.

in the communication quality based on the received signal strength indicator (RSSI). ASB tracks the current state of IoT communication protocols (e.g. Wi-Fi, LoRa) and keeps predicting their future RSSI. Then, switching is performed based on the RSSI prediction results - re-directs IoT app data to the switched alternate protocol.

ASB is well suited for a range of wireless devices - non-stationary personal devices (e.g. smartwatches, mobile, handsfree) and industrial autonomous devices (e.g. drones, warehouse bots). When such devices move out of the coverage area of WiFi 5 (5 GHz for higher bandwidth), ASB would have sensed this movement based on the RSSI prediction. Therefore, it will intelligently switch devices from WiFi 5 to WiFi 4 (2.4 GHz for long-range). As the distance from the router increases further, ASB will switch devices from WiFi 4 to LTE-M (CAT-M1, NB-IoT). Thus, ASB-equipped IoT devices are interoperable amongst multiple IoT communication protocols and resilient against communication breakdown. Example use-case:

When using high-bandwidth apps for live streaming, video calls, gaming, etc., smartphones are connected to the building WiFi over mobile data. When smartphones leave the building while using the apps, interruptions or service drops may encounter. Once WiFi is out-of-range, then the apps start using mobile data to reconnect and continue. In this commonly faced scenario, ASB senses the movement based on RSS predictions and will make smartphones seamlessly switch to mobile data, eliminating any service drops.

2.2 Porting & Execution of ASB on IoT Devices

In MCUs and small CPUs based tiny devices, the program space (flash memory) is always much greater than the available SRAM (e.g., Raspberry Pi Pico with ARM Cortex-M0+ has 16MB Flash, 264KB SRAM). So, we use our recent SRAM optimized approach [5], to produce a C version of the SVR ML model of ASB. This C version, during execution on boards (e.g., on Pycom FiPy in Figure 1), does not depend on the SRAM. Instead, it used the larger flash memory to enable the accommodation and efficient execution of larger ML models as well as TinyML models [6].

Similar to our scenario of porting and executing ASB on Pycom FiPy, when users apply this approach, they can successfully deploy and execute their ML models of choice on low-cost and low-power IoT devices that have only a few KB of memory.

3 EXPERIMENTS & INITIAL RESULTS

Figure 2 presents the experimental sites (at NUIG, DSI), and the designed Pycom FiPy [7] based hardware in Figure 1 over which we deployed the ASB. This FiPy device connects to the dual-band (supports WiFi 4, WiFi 5) access point (AP) and follows (a person walks with the device) the trace (yellow, red lines) via points (circled A to E). For example, at the NUIG site, the device is taken starting from circle A -> B -> C -> D -> back to A.

When FiPy was connected to WiFi 5, although it had higher bandwidth, throughout the travel (following the trace) of 14 minutes at the NUIG site, FiPy stayed without internet for 8.3 min. In the same scenario, when FiPy was connected to WiFi 4, although it has a better range (interference tolerance nature), FiPy stayed without internet for 6.7 min. But when ASB was activated, it predicted the future RSSI and efficiently switched between WiFi 5 and WiFi 4, leaving FiPy without internet for only 4.2 min. This is a 2.5 min improvement than only using WiFi 4 and a 4.1 min improvement than only using WiFi 5. Similarly, at the DSI site, throughout the travel of 11 minutes, with ASB activated, FiPy was disconnected for only 4.9 min. This is a 3.1 min improvement than only using WiFi 4 and a 5.4 min improvement than only using WiFi 5.

4 CONCLUSION & FUTURE WORK

In this work, we ported and executed an RBF kernel SVR based adaptive strategy (ASB) on a multi-protocol IoT hardware. The real-world experimentation demonstrated that ASB improves the resilience, interoperability, scalability of IoT devices by accurately predicting the future RSS in real-time and seamlessly switching to the wireless protocol with the best communication quality.

Future work plans to (i) Deploy ASB on a drone and investigate how it adds value to flying-IoT use cases such as long-range forest surveillance, life signs detector in disaster zones, etc., all of which demand high wireless communication quality; (ii) Fly the drone over Kilometers to examine ASB behavior under high-speed dynamic settings; (iii) Give IoT hardware access to global LPWAN networks, make the ASB perform switching between LoRa, Sigfox, dual LTE-M to verify whether ASB is location, protocol, and device-independent.

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