The Wiselib TupleStore: A Modular RDF Database for the Internet of Things

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Abstract

The Internet of Things movement provides self-configuring and universally interoperable devices. While such devices are often built with a specific application in mind, they often turn out to be useful in other contexts as well. We claim that by describing the devices’ knowledge in a universal way, IoT devices can become first-class citizens in the Internet. They can then exchange data between heterogeneous hardware, different applications and large data sources on the Web. Our key idea — in contrast to most existing approaches — is to not restrict the domain of knowledge that can be expressed on the device in any way and, at the same time, allow this knowledge to be machine-understandable and linkable across different locations. We propose an architecture that allows to connect embedded devices to the Semantic Web by expressing their knowledge in the Resource Description Framework (RDF). We present the Wiselib TupleStore, a modular embedded database tailored specifically for the storage of RDF. The Wiselib TupleStore is portable to many platforms including Contiki and TinyOS and allows a variety of trade-offs, making it able to scale to a large variety of hardware scenarios. We discuss the applicability of RDF to heterogeneous resource-constrained devices and compare our system to the existing embedded tuple stores Antelope and TeenyLIME.

1 Introduction

We are witnessing the evolution of Wireless Sensor Networks (WSN) into the Internet of Things (IoT), bridging the world of resource-constrained embedded devices to powerful machines and vast data clouds in the internet. Analysts predict enormous numbers of devices being connected to the Internet, for example, ABIresearch estimates 30 billion devices by 2020. To make this growth possible, hard- and software for networked embedded devices must become an easy-to-use commodity, especially when it comes to building complex applications.

To reach this goal, several demands have to be met: On the lowest layer, embedded devices have to be able to exchange messages and to identify each other using an agreed set of protocols, including a connection with the existing Web and its data pool. This is conducted—beyond other approaches—by the elaboration of standardized protocols like 6LoWPAN and CoAP, that map in a straightforward way to IPv6 and RESTful Web Services.

However, this is hardly enough: While these protocols define the means of communication, that is, how data is transferred, they leave it open to

https://www.abiresearch.com/press/more-than-30-billion-devices-will-wirelessly-conne
the application, exactly what is to be transferred. Consequently IoT applications today are often restricted to specific domains. A promising approach for data-layer integration is the idea to weave the IoT with the Semantic Web. The Semantic Web provides the tools and language to describe the real world using the Resource Description Framework (RDF) [?], a standard for encoding knowledge in a universal way that is extensible, machine-readable and can connect facts across different locations. It also is the basis of the Linked Data Cloud [?], where data from different sources in the Web is fused to become a unified and huge data set describing the world as we know it.

Most application continue to express data on the embedded device in a specific, limited vocabulary and adapt it to the Semantic Web standards only at a preceding proxy. This leads to a number of limitations: Embedded devices continue to be simple providers of sensor data, thus not allowing any direct exchange between embedded devices of different proxy domains. Furthermore, it makes it impossible to take a device operating in a network running some application and move it to another network running a different application. This is acceptable in today’s domain-specific applications, but not for the massive IoT networks we will see in the near future, installed and maintained by non-experts, who expect devices to be general-purpose and to be cross-compatible, just like any other computing device they are using. This is only achievable if devices are self-contained and independent of a specific infrastructure, requiring them to generate and process data without proxy components.

This paper introduces the Wiselib TupleStore, a flexible and portable database for efficient storage of RDF on embedded devices. It allows to quickly add RDF-processing capabilities to an application. The Wiselib TupleStore runs on many different platforms (including Contiki, TinyOS, Arduino/Wiring, Android, and iOS). It utilizes Flash memory where it is present, but can also store data in RAM when required. This enables applications that leverage the huge data sources available in the Linked Data Cloud, and that are no longer restricted by domain-specific languages (and “data silo” issues). We also show that there is little overhead to be paid for the generality, both energy- and storage-wise.

The Wiselib TupleStore is part of the SPIT-FIRE architecture [?], which includes 6LoWPAN, CoAP, RDF compression, and more, all available as platform-independent Wiselib components. This provides an easy way of building applications that use fused knowledge from the Semantic Web and embedded devices.

The rest of this paper is structured as follows: In Chapter 2 we will introduce the challenges accompanying our idea and discuss related work. In Chapter 3 we present the architecture of our system before we provide details about our compression methods in Chapter 4. Finally in Chapter 5 we compare our solution to the well-known embedded tuple stores Antelope and TeenyLIME and then conclude in Chapter 6.

2 Problem Statement and Related Work

Devices in the IoT are diverse and heterogeneous in several aspects. The IoT vision strives to integrate these devices not only with each other but also with the current Internet in order to create a universal web of knowledge covering both static data and live observations. Depending on vendor, application purpose and deployment context devices may differ vastly in terms of utilized hardware. Thus a variety of combinations of processor types, available memory, means of communication and energy constraints is encountered in the field. Additionally, a variety of operating systems, middlewares and applications for these devices are already in daily use. Some of them support multiple devices, Contiki [?] and TinyOS [?] being probably the most prominent representatives of this class. We also encounter proprietary systems specifically designed for a rather limited set of hardware platforms. In addition to this diversity in terms of hardware and software we observe varying deployment contexts and usage scenarios of these devices.

We raise the question of how these devices can be integrated in a meaningful way such that knowledge can be shared across varieties hardware, software or application contexts in order to allow universal auto-configuration and a style of application development that can make use of data located in the Web as easily as live sensor descriptions. This breaks down into several sub-problems:
2.1 Component Portability

The plethora of available devices has led to a patchwork of individual solutions for each device, tailored to the system specifications. Contiki and TinyOS have been developed as embedded operating systems which run on several hardware platforms to ease up this situation. Still, software components often are only available for one OS. For the application developer, porting code to all target platforms and maintaining parallel software lines is required. Because of this fact, we use the Wiselib [?] as foundation for the Wiselib TupleStore. The Wiselib is a platform-independent algorithms library for embedded devices, running on a multitude of platforms and operating systems (including Contiki, TinyOS, Arduino, iSense, OpenWRT, and many more). It is modular by design, allowing an application to find the perfect balance between data structure capabilities and resource efficiency. By building on the Wiselib, the Wiselib TupleStore can be compiled and optimized for a wide range of platforms, making it widely available for future applications.

2.2 Standardized and Open Data Layer

Even given physical interoperability, common communication protocols and data serialization formats, applications on different devices can not necessarily exchange data successfully. While serialization formats provide structure for data, content and semantics stay undefined and thus different for every application. Several standardization efforts have been made to agree on a common data layer: The Open Machine Type Communication Platform (OpenMTC) [?] provides machine-to-machine (M2M) communication methods on top of several standardized protocols and provides features such as service discovery, routing and notification. OpenMTC defines a set of XML schemas that can describe sensors and actuators in several aspects. Although exhaustive, this approach is limited to a certain descriptive domain and does only provide user-given device annotations via tags with limited descriptive capabilities.

How to convert the often compactly and proprietary communicated sensor data to semantic documents has been answered by a multitude of proxy-oriented approaches [?, ?, ?, ?]. The Open Geospatial Consortium (OGC) published the Sensor Observation Service (SOS) [?] a standard for web service interfaces to sensor networks, defining a set of XML schemas describing sensor meta data, observations or geography. As an extension to SOS, Henson et al. introduced SemSOS [?], proving a bridge to the Semantic Web and allowing advanced semantic queries and semantic reasoning. Internet Connected Objects for Reconfigurable Ecosystems (iCore) [?] is a project funded by the European Union that proposes such a proxy-based framework that composes semantic descriptions of embedded devices into semantic descriptions of observed real-world objects [?]. All of these have in common that the exposed data will not carry universal semantics before being transformed by the proxy system, making the device inherently depending on its proxy to be useful.

2.3 Independence of Translating Infrastructure

In order for embedded devices to be useful independently of a supporting infrastructure and thus utilize the semantic data on the device for universal auto-configuration and communication between embedded devices, it is necessary to manage a certain amount of data on the device itself. Sadler and Martonosi have developed a database for embedded devices that is tailored for usage in Delay Tolerant Networks (DTN) [?]. Distributed tuple spaces have been presented in the TeenyLIME [?, ?] and Agilla [?] systems, which are available for TinyOS. Recently, Tsiftes et al. [?] have introduced a relational database for devices running the Contiki operating system. All of these allow managing general-purpose data, however do not feature compact representation of RDF data. As RDF in its common serializations (such as RDF/XML and N3) tends to be quite verbose, efficient compressing storage schemes are crucial to employ semantically self-describing embedded devices.

2.4 Resource Constraints.

When storing data on embedded devices, one has to overcome strong resource constraints. Many sen-
Sor networks are battery powered, making energy an extremely critical resource. Therefore a storage system has to ensure that operations to store, delete or access the data will not result in excessive battery drain. Other systems might be equipped with a considerably restricted amount of memory, sometimes even shared with operating system and program code. Therefore, a database system which aims to store RDF data on embedded devices profits from lightweight compression techniques for saving both energy and space. Compression of RDF data has recently been addressed by Fernández et al. [?], with the Header-Dictionary-Triples approach that compresses tuple elements into a dictionary, followed by a compressed representation of triples of dictionary keys. This approach however can only be successfully applied to large data sets and focusses on serialization in the sense that it is not well suited for updating the compressed RDF on tuple-level. Su and Riekki [?] proposed an approach for producing RDF on embedded devices by the use of templates, that is, a predefined set of statements containing place holders to be filled in with e.g. current sensor values. This approach however assumes a known structure to the semantic data that is to be expressed which contradicts our demand on the ability of expressing arbitrary and possibly unforeseen facts.

3 Architecture

When designing a software architecture for the IoT, a multitude of different platforms has to be considered. These platforms not only differ in processing speed, but also vastly wrt. memory size and available energy. In an IoT network, an application is likely developed under constraints on available energy and the amount of data it must be able to store and/or process. If the task at hand involves a certain amount of communication, it might be worthwhile invest some energy for compressing data. For applications that do not transmit a lot of data, the maintainer might decide to avoid the energy cost of an encoding mechanism altogether and reduce the code size instead. In order to satisfy these high demands on flexibility, a modular architecture is essential. In this section, we will illustrate the different components of our architecture and show how the choice of their assembly allows trade-offs between memory footprint, code size and energy consumption.

3.1 The SPITFIRE Software Stack

In our vision of the IoT, knowledge on the Web as well as (live) descriptions of embedded sensing devices are encoded in RDF and interlinked with each other across physical domains. The SPITFIRE project realizes this vision with a stack of components shown in Figure 1. The foundation for managing RDF data on the embedded device is the Wiselib TupleStore allowing the device to work with RDF data on a tuple level. On top of that, the Wiselib RDF Provider [?] enables a document view, a notification mechanism and several pluggable RDF serializations and communication protocols. These communication mechanisms can be utilized to access data in the Wiselib TupleStore electively on a tuple- or document level. Moreover the communication interface allows connecting the embedded device to a Smart Service Proxy [?] instance which can expose the descriptions of the device to the Semantic Web and allows a user to query the embedded devices using SPARQL [?] over standard web services, providing for caching, push/pull mechanisms, format translation and several other features.

3.2 TupleStore Functions

We designed the TupleStore as a flexible and lightweight data storage that provides the following operations: insert inserts a new tuple into the store, query finds tuples matching a tuple template.

![Figure 1: Simplified view of the SPITFIRE architecture: The Wiselib RDF Provider and the Wiselib TupleStore provide RDF on tuple- and document level on the embedded device. The Smart Service Proxy then connects the embedded network to the Semantic Web.](image-url)
with wildcards and erase erases a given tuple from the tuple store. For enabling lightweight configurations, the Wiselib TupleStore core offers only restricted means of querying through the query method described above. The SPITFIRE architecture provides two components on top of the Wiselib TupleStore that allow a more sophisticated tuple selection: The Wiselib RDF Provider provides the view of (potentially overlapping) documents, that is, sets of tuples. Additionally, SPITFIRE offers also an in-network query processing mechanism which also includes a local component that can be used for more complex queries.

### 3.3 Components

In order to implement the TupleStore in a modular and resource-efficient manner, it is crucial to reduce the cost of modularity to a minimum. Mechanisms such as runtime dispatch of method calls (as in C++’s virtual inheritance mechanism) are undesirable, as they add overhead at runtime (and thus energy consumption) and code size, even if it is known at compile-time which modules are to be selected. Also, such mechanisms create optimization barriers, i.e. disallow the compiler to apply optimizations such as method inlining. We rely on the modularity approach of the Wiselib: Components are implemented as templated C++ classes, called models. They are instantiated by the compiler, receiving operating system specifics as template parameters. This way, a component that is not being used will never be instantiated, i.e. the component will not use any code space. This allows for a high degree of modularity without code size or runtime penalties. As typical in the Wiselib, we use concepts to define the interfaces of our components. Concepts describe properties of models. We briefly introduce our components, some of them grouped together for brevity. A conceptual overview of the interactions of the components is given in Figure 2.

#### 3.3.1 Tuples

Depending on the source of the data that is to be inserted into the TupleStore, different internal tuple representations might be appropriate. E.g., certain elements might be generated on demand or be the same for a huge number of tuples. For this reason, TupleStore components do not force their users to use a specific tuple implementation but provide templated methods that accept any type adhering to the Tuple concept. This concept requires anything that is to be accepted as tuple to implement the following methods:

- **size** Report the size (number of elements) of the tuple.
- **access** Access a given tuple element (read/write).

#### 3.3.2 TupleStore

The TupleStore component provides the operations insert, erase and query using a container model to hold the tuples as well as a selectable dictionary implementation for holding the tuple elements. Depending on the memory management capabilities.
of the platform, a user would typically use either a static vector or a dynamic linked list as tuple container, however other containers such as dynamic vectors or set implementations are also possible. In addition to these RAM-based data containers, the user may also decide to store tuples on a block device such as an SD cards, using a container implemented as a external hash set based on the B+ tree [?], see Figure 3 for illustration. Internally, the actual stored data the much more space-efficient dictionary keys that point to corresponding entries. The TupleStore will ensure that on read access, the element values are fetched from the dictionaries transparently such that the user is not concerned with the dictionary mechanism.

It is possible to configure (at compile time), which elements of a tuple will be managed using the given dictionary, which enables avoiding unnecessary dictionary operations on value types for which they are not profitable (e.g. integers). If the code size and/or runtime overhead for dictionary compression is not considered reasonable, it can be switched off altogether, yielding a TupleStore that stores tuples in its container “as-is”.

### 3.3.3 Dictionary

The task of a dictionary is the efficient storage of tuple element data. Dictionaries provide methods for inserting data (returning a corresponding key), for data access by key and for data deletion. A dictionary can, in several ways, exploit redundancies in the stored data in order to reduce memory usage. We implemented three dictionary models: The AVL Dictionary, the Prescilla Dictionary and the Chopper Dictionary, all of which compress data by storing for each element a count such that elements occurring multiple times only need to be stored once. Similarly to the tuple container, we also provide a block-storage based dictionary implementation based on the B+ hash set described in Figure 3 which can be exchanged transparently with the RAM oriented dictionaries. See Section 4 for an in-depth discussion on the compression schemes used in the dictionaries we implemented.

### 3.3.4 Codec

Given a codec, the Wiselib TupleStore transparently encodes/decodes data (i.e. tuple elements), such that internally only compressed/encoded data is stored while the user can work with plain text data and does not need to be concerned with the encoding process. It is however also possible to directly access the encoded data such that it can be transferred to other nodes without the need for a decoding operation. In Section 4 we will introduce in detail our Huffman codec that compresses data using a predefined Huffman tree. In contrast to the dictionary approach, a codec does not store any tuple elements but rather transforms them between plain and encoded format.

### 4 Compression Components

RDF data consists of (Subject Predicate Object) triples, whereas the triple elements are either URIs, literals or local identifiers. As identifiers, URIs and string literals usually have a relation to natural language, their symbols are likely to be unequally distributed, that is, some symbols are more likely to be encountered than others. Furthermore, few subjects (be they referring to abstract concepts or real-world objects) can be described sufficiently with a single triple, that is, repetition of elements is to be expected in realistic RDF data. When elements share a (semantic) domain in the sense that they are related in meaning, it is likely the case that they also share common URI prefixes. These different types of redundancy can be efficiently exploited by a combination of element-wise and cross-element compression mechanisms which we present in the following sections.

#### Huffman Coding

A standard approach for string compression is Huffman coding [?], a variable-length encoding that depends on the distribution of plain text symbols. The codec is represented in form of a binary tree with plain text symbols in the leaves. For each of these plain text symbols, the unique path to the root of the tree yields the corresponding code symbol. The tree is formed by arranging all possible plain text symbols according to their frequencies in the data such that the most frequent plain text symbols are encoded with the shortest codes. It has been shown that the application of Huffman coding can lead to significant energy savings as the
size of transmitted messages can be reduced. See for example the works of Yeo et al. [?] or Yuanbin et al. [?]. Our approach uses succinct trees [?] to store the Huffman tree with high space efficiency. Succinct data structures focus on storing data with a space efficiency, as close as possible to the theoretical limits. Arroyuelo et al. [?] give a detailed overview about available succinct tree implementations in their work. Our codec manages a compact Huffman tree in 416 bytes of storage that is defined for the whole ASCII alphabet and can thus be used to compress and decompress any tuple element.

**AVL Dictionary**

For storing repeated tuple elements (be they strings, integers or any other data type), we add reference counting to the stored elements. To find the element record and the associated count, we need a data structure to keep track of all those records. By using the well-known approach of AVL trees [?], we obtain a dictionary that can guarantee to do insert and delete operations in \( O(\log n) \) element comparisons, where \( n \) is the number of inserted elements. By using the memory addresses of nodes holding element values as dictionary keys, we can additionally guarantee a value lookup by key in \( O(1) \).

**Prescilla Dictionary**

As RDF data tends to have a high amount of common prefixes, element comparisons in the AVL tree repeatedly compare the same prefixes in different elements, thus making the runtime also dependant on the average element length. The Prescilla Dictionary utilizes a variant of the radix tree (or PATRICIA tree), a trie data structure originally introduced for text indexing [?]. The constructed tree does not hold complete elements in its nodes but substrings such that the concatenation of node values along a path from a root to a leaf forms a string present in the dictionary. Our data structure contains several optimizations over the radix tree to make it more efficient for use on resource-constrained embedded devices. Like with the AVL Dictionary, by using the memory addresses of nodes holding element values as dictionary keys, we can additionally guarantee a value lookup by key in \( O(1) \).

**Chopper Dictionary**

Both the AVL dictionary and the Prescilla dictionary provide a tree structure holding variable-sized data in the nodes. Thus, in order to create a new node, a sufficient amount of memory must be allocated and freed again when the node is not needed anymore. This kind of memory management is available on some platforms either in hardware or software, for example the iSense operating system supports `malloc()` and `free()` in the usual libc style. Some platforms, such as Contiki (e.g. on the TMote Sky) do not feature such a mechanism. The Wiselib does provide memory allocators to compensate for this, however, software allocators naturally come with a certain overhead in terms of CPU usage (for allocation) and memory usage (for supporting data structures and fragmentation). In order to address this issue, we provide the Chopper Dictionary which does not require dynamic memory allocation. The key idea is to only handle fixed-size chunks of strings in a statically allocated table. In order to connect the different chunks to a complete string, special meta chunks are inserted that do not contain string data but references to string chunks in order to encode longer strings. While this approach can in general not exploit all common-prefix redundancy present in the data due to the fixed-size string partitions, its very low overhead (one additional byte per chunk, no dynamic allocation needed), make it a useful asset for heavily resource-constrained devices.

5 Evaluation

In this chapter we investigate the features and performance properties of the Wiselib TupleStore in comparison with existing embedded databases Antelope and TeenyLIME. While we are convinced that these approaches are impeccable for storage of short fixed-length data, such as numeric values, we hope to illustrate that for the storage of RDF, the Wiselib TupleStore offers certain advantages.

First, we will briefly discuss the datasets we considered and the effectiveness of our compression mechanisms on them. We then discuss the modularity and code size of different Wiselib TupleStore configurations. Finally, we evaluate execution times and energy consumption of the Wiselib
TupleStore operations and compare them practically to TeenyLIME and Antelope.

5.1 Datasets

In order to address the diversity of RDF descriptions found in different application contexts, we consider three different datasets for analysis of our compression components:

**BTCSAMPLE** This dataset is a random selection of 4796 triples from the Billion Triple Challenge (BTC) 2011 with an uncompressed file size of 1040kB. As the Billion Triple Challenge targets at collecting large numbers of triples, this excerpt is very diverse in terms of contents. We thus expect very few repetitions of tuple elements and also few shared prefixes, in this regard the BTCSAMPLE dataset will provide a hard compressible RDF dataset.

**SSP** The Smart Service Proxy (SSP) dataset was assembled using the output of an instance of the Smart Service Proxy, a software system that converts the output of over 300 real sensors into semantic descriptions. The output consists of 4859 triples and has a total size of 883kB. Most of the URIs share as a prefix the URI of the service, which we expect to be beneficial for compression.

**NODE** The NODE dataset contains a typical RDF description of a single sensor node. It describes a temperature sensor with its measured value, unit of measurement, value range, and method of measurement (stimulus). The dataset has been generated using the publicly available LD4Sensors web application. The generated RDF file holds 73 triples and has a size of 7.6kB. Due to its suitable content and size, we will conduct the evaluations on the TMote Sky devices (see next chapter) using this dataset.

![Figure 4: Distribution of string lengths (bytes) of RDF elements for our datasets.](image)

5.2 Compression

Figure 5 shows the effectiveness of our different compression approaches: As the prefix commonalities differ notably between different datasets, while the effect of Huffman compression is much more independent from the chosen dataset and reliably saves about 30 to 35 percent storage space. Adding a Prescilla dictionary drastically changes the picture (Fig. 5c): For BTC and NODE the compression ratio has decreased due to overhead and the lack of many common prefixes, while for SSP 72.5 percent of the data can be compressed.

5.3 Heterogeneity and Code Size

The Wiselib TupleStore offers a multitude of configurations which allow different trade-offs in terms of code size, RAM usage and energy consumption. On the lower end of the code size scale, we have a feature-minimal TupleStore configuration that still allows insert, deletion and querying of tuples on multiple platforms. For code size considerations, we compiled the same source code for different platforms (see Table 1) and calculated the difference in size to an empty Wiselib application in order to obtain the code space consumption of the individual component. As it is not possible to instantiate all components usefully standalone, we take a cumulative view on the components, i.e. add them up one after another and/or exchange them so we can reason about the code size difference of that particular step.

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[4] http://km.aifb.kit.edu/projects/btc-2011/
[5] https://github.com/ict-spitfire/smart-service-proxy
[6] http://spitfire-project.eu/incontextsensing/ld4sensors.php
Figure 5: Left: CDF of common prefix lengths across all pairs of elements for each data set (higher is better compressible by dictionaries). Center: CDF of saved bits when compressing element-wise using the Huffman codec (higher is better compressible by Huffman). Right: Overview of our datasets in compressed form.

| Platform          | Codecs & Dictionary | Antelope |
|-------------------|---------------------|----------|
|                  | TS only             | Prescilla| AVL | Block | Prescilla| AVL | DB Kernel |
| iSense 5139       | 3332 / 32           | 5780 / 36| 8948 / 40 | -     | 9960 / 36| 13184 / 40| -     |
| iSense 5148       | 1828 / 28           | 3444 / 36| 5112 / 40| 13600 / 11072 | -     | 5840 / 40| 7568 / 40 | -     |
| Contiki/MicaZ     | 3490 / 13           | 5910 / 16| 8562 / 18 | -     | 9462 / 433| 12120 / 435| -     |
| Contiki/TelosB    | 1634 / 14           | 3710 / 16| 5022 / 18 | -     | 5962 / 18| 7282 / 20 | -     |
| TinyOS/TelosB     | 1526 / 14           | 3534 / 16| 4786 / 18 | -     | 5792 / 18| 7050 / 20 | -     |
| TinyOS/MicaZ      | 3490 / 13           | 5910 / 16| 8544 / 18 | -     | 9462 / 433| 12102 / 435| -     |

Table 1: code sizes for various platforms and configurations. (The notation is “ROM / RAM”. For example, on TelosB we can provide a TupleStore featuring insert, delete, and query in 1.6kB of code size.

5.4 Execution Times and Energy Consumption

We evaluated the Wiselib TupleStore in terms of execution time and energy consumption of its basic operations insert, query and erase. To our knowledge, the Wiselib TupleStore is the first multi-platform embedded database optimized for storing RDF. As it still can be used for general tuples and thus might be considered a general purpose embedded database, a comparison to existing embedded databases seems natural. We consider Antelope, a flash-based flexible general-purpose relational database for the Contiki operating system as well as the local, RAM-based storage of the TeenyLIME, a distributed tuple space for TinyOS. As all systems include the TMote Sky as possible target platform, we use it for comparison. The experiments were conducted on the w.iLab.t Testbed provided by the CREW project located in the iMinds research center. The testbed is equipped with 193 TMote Sky Sensor motes with 10kB RAM and 8MHz MSP430 processors. The motes are connected to a programmable system that can be used for energy measurements and the simulation of sensor value inputs to the node. As input data we considered the NODE dataset described in Section 5.1. As Antelope and TeenyLIME do not feature storage of variably-sized strings, we configured them to account for strings of a maximum length of 120 characters, which, as Figure 4 illustrates, is sufficient for most (but not all) RDF elements in our datasets and all elements in NODE. This gives a bit of advantage to these implementations, as we allow them to reject some valid data. TeenyLIME was given 6240 Bytes of RAM to use for Tuple storage, the Wiselib TupleStore was configured with a tuple container with 76 elements and a Chopper Dictionary with 100 entry slots, each 15 bytes, thus using a total of 2512 bytes of RAM.

In order to compensate for call overhead, triples were inserted in groups such that their unencoded
size did just not exceed 1kB. This approach had to be slightly adapted for the TeenyLIME test to account for a smaller number of tuples that TeenyLIME can manage. With the tuples inserted we issued query and erase commands both with random, findable tuple patterns containing one wildcard at a random position as input (e.g. \(<\text{http://...}>\ <\text{http://...}>\ *\) ). The observed distributions of energy consumption of the different tuple store operations are depicted in Figure 7 and that of the execution times in Figure 6.

Antelope does not provide a built-in string comparison routine, thus queries for Antelope were substituted with a simple routine that iterates over all tuples and compares them for equality using strcmp(), taking wildcards into account. As it is not possible to select tuples by string value equality in Antelope, we could not evaluate the erasure of tuples in that database in a meaningful way. We note that it is possible to substitute this missing functionality with selecting all non-matching tuples, insert them into a new relation and then free the old relation, which is similar to what Antelope does internally on deletion of (non-string) tuples.

The TMote Sky platform features 1024kB of external flash, composed of 16 segments a 64kB which is used in combination with some of the available RAM by Antelope to store tuples. The “zig-zag” shape of the Antelope insertion execution time and energy consumptions can be thus be explained by caching and flash I/O semantics (e.g. tuples being cached in RAM and only written to external memory when there is no space left in RAM). Furthermore, we observe that only two sets of tuples (4 tuples each) could be inserted for the TeenyLIME configuration, as the third group of inserts already exhausted the available memory and was only partially inserted. It might be possible to tweak TeenyLIME to a more efficient use of the available memory (e.g. by finding a good value for the memory slab size). Due to the (uncompressed) way TeenyLIME handles string data however, it could not possibly fit more than \(\left\lfloor\frac{6240}{(3 \times 120)}\right\rfloor = 17\) tuples in RAM (neglecting all potential overhead induced by data structures and metadata).

Figures 6 and 7 give an overview over execution times and energy consumptions of the three Wiselib TupleStore operations, respectively. Due to its higher complexity and greater storage space (in terms of tuple count), insertion in the Wiselib TupleStore costs notably more time and energy than in TeenyLIME and is comparable to Antelope (which however, operates on external flash). In terms of lookup, TeenyLIME is notably faster, but Wiselib TupleStore seems to provide the most energy-efficient lookups. We believe this efficiency to be related directly with the dictionary approach: During a query, each element string needs to be looked up only once, after it is located, the Wiselib TupleStore seeks to locate a matching tuple of dictionary keys. In contrast in TeenyLIME, the elements of the query tuple have to be compared to elements of all other tuples until a matching tuple is found, resulting in higher energy consumption, the analogue holds for erasure of tuples by template, which boils down to executing a query followed by a relatively inexpensive delete operation.

From the experiments we conclude that there is an overhead to be paid for using the Wiselib TupleStore, however it is reasonably small. Our database for arbitrary string-based RDF data uses about as much energy and runtime as much simpler tuple spaces with fixed record size, but opens the door to much richer applications.

6 Conclusion

By enabling embedded devices to describe their state and their observations in the universal RDF format, these devices can be integrated into the Semantic Web. This allows not only for easy machine-to-machine communication but also (in conjunction with other components) for posing queries that combine information from the sensor network and documents in the web. To show that this idea is feasible, we introduced the Wiselib TupleStore. The Wiselib TupleStore provides a potent mechanism for managing arbitrary RDF data on resource-constrained embedded devices. Due to its portability and modularity it can be set up to utilize flash memory or RAM and adopt to the capabilities and resource constraints of almost any given device. In experiments comparing it against TeenyLIME and Antelope, we have shown that energy and runtime cost is reasonable, especially considering that our implementation can work with arbitrary data, and runs without code porting on many different platforms.
Figure 6: Execution times for tuple operations for Antelope (on flash storage, blue-dashed), TeenyLIME (in RAM, green) and the Wiselib TupleStore (RAM, black, straight line). Left, Center: **insert** and **query** with different number of tuples present in the store. Right: **erase** dependant on the number of tuples already erased (0 equals 73 tuples present in Wiselib TupleStore and 12 in TeenyLIME).

Figure 7: Energy consumption for tuple operations for Antelope (on flash storage, blue-dashed), TeenyLIME (in RAM, green) and the Wiselib TupleStore (RAM, black, straight line). Left, Center: **insert** and **query** with different number of tuples present in the store. Right: **erase** dependant on the number of tuples already erased (0 equals 73 tuples present in Wiselib TupleStore and 12 in TeenyLIME).