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Proportional throughput differentiation with cognitive load-control on WSN channels

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Abstract

Wireless sensor networks are nowadays used in various applications to facilitate monitoring and actuation tasks, e.g., for smart grids and industrial automation. Some of these applications require guarantees or at least assurances on reliability. Such applications expect predictable throughput and delay, which are hard to maintain in environments with changing radio conditions. QoS-aware MAC protocols capable of handling such environments are well explored. They require however protocol changes and are therefore difficult to deploy. This paper presents an application layer forwarding service that offers proportional differentiation while limiting network load to preserve high utilization and predictability. Demands for capacity are expressed as fractions of the overall channel throughput. We show that this service can be implemented with a cognitive load controller (CLC) based on fuzzy logic and quality assessed with utility functions for application layer packet loss and throughput. We evaluate the CLC for 802.15.4 with CSMA/CA through NS-3 simulations showing that it offers the intended service while adjusting load for high overall throughput and low delay.

Keywords: WSN; Fuzzy logic; Differentiation

1 Introduction

Smart grid applications that can benefit from wireless network communications include automatic meter reading, remote system monitoring, and equipment fault diagnostics [1]. Such applications need to work in harsh and complex electric-power-system environments that challenge the reliability of WSN communications. Industrial network communications for factory automation need to support a multitude of applications [2]. Communications for smart grid and industrial applications involve data acquisition from devices and sensors at key positions as well as messaging for device control and actuations. For some devices, data is preferably communicated wirelessly, in wireless sensor networks (WSNs). Wireless communications are especially attractive in harsh environments where wiring for communications is difficult and costly and where wires may easily get damaged.

Multi-hop WSNs in which data is transmitted more than once over the wireless media brings several advantages including self-organization, flexibility, and self-healing capabilities attractive for applications demanding availability. Although benefits brought by multi-hop such as redundancy and self-healing, single-hop configurations are sometimes preferable. Such cases include when devices are within reach of wired infrastructures or some of the devices are capable of one-hop long-range communications, e.g., over 3/4G cellular networks [3]. This is because successfully delivered packet then traverses the radio media only once and does not consume battery and transmission capacity twice or more. Multi-hop WSNs using different channels for consecutive hops suffer less from this multiple capacity use and are hence preferable when single-hop WSNs are insufficient.

This paper focuses on the single-hop case for each channel in WSNs. The main contributions are (1) the definition of a proportionally rate-differentiated service for single-hop WSNs that can be implemented at application layer or in middleware together with load control for high network utilization and predictability and (2) the design, implementation, and evaluation of an application layer CLC for this service, easy to deploy with off-the-shelf 802.15.4 CSMA/CA (carrier sense multiple access with collision avoidance) MAC software and hardware without extensive additional signaling.

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A dependable communication system for smart grids and industrial automation relies on predictable transmission rates and network quality of service (QoS) for time-sensitive data delivery [2]. Transmission rates in WSNs can however be hard to know before deployment and extensive testing, especially for wireless networks such as IEEE 802.15.4 [4]. This network technology is attractive due to its low-power consumption although it offers limited capacity, typically peaking at around 200 kbps and considerably less at overload when many individual nodes try to use the channel simultaneously [5]. The use of different channels alleviates the overload problem. Avoiding overload remains however important for each channel to make the most of available transmission capacity.

The need for transmission predictability in WSNs has driven research on QoS-aware MAC protocols capable of supporting predictable transmission rate in environments with changing radio conditions and moving object impacting on transmission quality [6–8]. The IEEE is working on standardizing the 802.15.4e which includes time-slotted channel hopping for better support of industrial applications [3]. Also, cross-layer approaches have been shown to help in improving effectiveness and predictability of WSNs [9, 10]. Although tweaking MAC protocols and possibly adjacent protocol layers provide attractive network properties, such solutions come at the cost of protocol changes and imply to abandon widely used and tested protocol implementations. This motivates a middleware or an application layer approach for predictable service, which can be implemented with off-the-shelf MAC hardware and software.

Predictable transmission rates may be understood as strong assurances or even guarantees on throughput, delay bounds, or a combination of those [11–13]. A more relaxed service model is herein presented, which aims at proportionally distributing forwarding capacity to wireless devices based on stated demands. This service model allows for pairing load control with needs for predictability to offer high utilization of wireless channels, low delay, and demand-based distribution of available forwarding capacity. Consequently, the actual throughput offered to devices will vary with the overall throughput, which means that stronger assurances need be provided internally by devices instead of as a network service. For example, mission-critical messages can be scheduled at devices for transmission with strict precedence over other messages.

This paper further presents the design and evaluation of a CLC that provides proportional throughput differentiation between devices. The CLC requires devices to strictly limit transmission rates to their offered forwarding capacity, which will match the demanded part of the overall channel throughput. Devices will send at these full rates defined for each device and measurement period until the CLC finishes its load adaptation. Thereafter, the devices can send at any rate up to their respective upper limit found through the load adaptation made by the CLC. The load adaptation needs to be repeated in case the distribution of demands for capacity alters or if radio conditions change, e.g., due to devices that are re-located.

The CLC is based on fuzzy logic and assesses channel load with utility functions for packet loss and throughput of each individual device. The mechanism is evaluated for 802.15.4 through NS-3 [14] simulations showing that it can offer the desired proportional differentiation while limiting the collective load to ensure high network utilization and low delay. We discuss how this mechanism can be implemented for resource-constrained networks such as 802.15.4 without requiring extensive signaling of variables for the mechanism itself.

The rest of the paper is organized as follows. Section 2 presents related work on QoS and approaches to battle congestion in WSNs as well as previous work on proportional differentiation models. Also, related work that includes fuzzy logic is presented. Section 3 discusses application needs for service predictability, needs for load-control and introduces the proportional differentiation service model in focus of this paper. Section 4 defines the CLC mechanisms, while Section 5 presents our evaluation of its properties. In Section 6 is implementation aspects discussed regarding variables updates, perceived quality assessment, and transport of data for the CLC. Section 7 presents future work with focus on proportional differentiation in multi-hop WSNs. Finally, the paper is concluded in Section 8.

2 Related work

Differentiation and network QoS in wireless sensor networks (WSNs) have been extensively researched over the past decade and more. Chen et al. [15] gave a survey of QoS in WSNs where research efforts are identified in the areas of routing over multiple wireless hops for end-to-end QoS, reliability assurance, and application specific QoS. They identify needs for further research on satisfying QoS requirements while ensuring efficient resource usage at network overload, which this paper addresses.

Many QoS-aware MAC protocols for WSNs address how to satisfy QoS requirements and ensure efficient resource usage at network overload [6–8]. They require however changes to off-the-shelf MAC hardware, software of both. Cross-layer approaches to improve effectiveness and predictability in WSNs as surveyed in [9] and explored in [10]. These approaches also affect adjacent protocol layers, which means comprehensive changes to WSN protocol stacks developed, tested, and deployed in smart grid and industrial production contexts and elsewhere. Instead of adapting the MAC layer or other layers below the application socket interface, we restrict our differentiation service model and implementation to the application layer or middleware. Thereby, it can be created with off-the-shelf hardware and software for available transport layers and below.

Our work differs further from previous research in QoS-aware MAC protocols and cross-layer solutions in that we aim for a more relaxed service model compared to those targeted by MAC-centered solutions for QoS in WSNs. Our service model aims at proportionally distributing forwarding capacity to WSN devices based on stated demands instead of offering strict guarantees or assurances on certain transmission rates. Thereby, it requires less detailed information on network status and can be implemented entirely at the application layer or in middleware. Also, it is less sensitive to changing radio conditions and demands for capacity since the actual throughput assurances are relative to each other and not related to requests for specific transmission rates.

Proportional service models are well explored and previously presented in the context of loss rate and delay differentiation for congestion responsible applications using TCP in wired IP-based networks [16–19]. Wang and Ramanathan further presented mechanisms for proportional delay differentiation in wireless IEEE 802.11-based ad hoc networks [20]. Proportional throughput differentiation for constrained IEEE 802.15.4 WSNs is however not explicitly studied previously.

Proportional loss rate and delay differentiation is of limited use in WSNs since applications commonly use UDP for transporting messages. For example, the Constrained Application Protocol (CoAP) runs over UDP and implements its own mechanism for reliable transport in [21]. Although congestion control is considered for CoAP [22], we chose to focus on proportional throughput differentiation for the service model defined herein. We motivate this by throughput differentiation that addresses the common use and current standard track approach for protocols such as CoAP.

Several approaches have been proposed to battle sensor network congestion, with different means to detect congestion. In [23], the authors aim at fairness by having a congestion control unit distribute data rates equally among downstream nodes. Liang and Gao [24] analyzed current queue lengths and oscillations as signs of congestion. In [25], aggregate input and output data rates were studied. Based on a fairness factor, they allocate capacity among nodes. Paek et al. [26] used time to recover loss as congestion indicator. Although application layer or middleware information on WSN load is less precise than looking into lower layer parameters, in our solution, we avoid using other information but loss rate and throughput seen above the network socket interface. This allows for implementing it without changes to off-the-shelf hardware and software for transport layers and below.

Papers related to fuzzy logic include [27], where Ali El Masri et al. adapt rates based on packet delay and buffer size. The results showed that their traffic regulation mechanism supported QoS. In [28], threshold management of buffers is realized with fuzzy logic. They defined fuzzy cases that determine how much buffer is occupied and how many packets are rejected. In [29], the fuzzy logic system provides high throughput under low latency. It aggregates packets in the buffer at busy channel, and buffer delay is distributed among nodes resulting in high performance for voice transmissions. Recently, a fuzzy logical controller for priority-based rate control in multiple-hop WSNs is presented in [30].

Fuzzy logic controllers are also used in several other applications where low decision-making cost is desired. For example, in [31], fuzzy logic is applied for web-based self-learning and self-adapting outer loop speed control for permanent magnet synchronous motors (PMSMs). The work of Zhou et al. is based on Takagi-Sugeno fuzzy logic system approximating the optimal control law for the speed control of the particular PMSM that is to be controlled [32, 33]. Fuzzy logic has further been used to control network functions such as routing [34] and admission control [35].

Our work differs from previous research in several aspects. Based on lightweight observations of per-node throughputs and loss rates, we assess impacts from network load on application usefulness through utility functions. Our CLC is based on fuzzy logic and provides proportional throughput differentiation between devices in a WSN while ensuring high network utilization and low delay when applications would overload the network without load control. The CLC was firstly presented and evaluated regarding network utilization, adaptation delay, and lower layer variables for load assessment in [36]. This paper contributes further with definition and evaluation of proportional throughput differentiation based on this load control mechanism, as well as further evaluation of the CLC properties, implementation aspects, considerations for its practical deployment, and future work on the presented differentiation model.

3 Service predictability and differentiation

Applications for smart grid monitoring and controls as well as applications for factory automation can be assumed to adapt their sending rates to control the load on shared networks like IEEE 802.15.4 CSMA/CA WSNs. Controlling the load is beneficial for network efficiency and can be associated with proportional differentiation to provide additional value to applications for automatic meter reading, remote system monitoring, equipment fault diagnostics, and other data acquisition tasks.

3.1 Application needs for predictability

Smart grid applications such as automatic meter reading, remote system monitoring, and equipment fault diagnostics require reliable two-way WSN communications between electric utilities and the customerŠs metering devices [1]. Furthermore, monitoring systems based on smart sensor nodes and WSNs can provide important information on the conditions of system components, including generation units, transformers, transmission lines, and motors. Part of such information can be especially important and hence need reliable and predictable delivery at short delay. Proportional rate differentiation can provide such predictability to wireless nodes for them to internally ensure that essential information is given precedence by the application or between applications deployed on the same node. This would mean to let the applications decide to communicate less urgent information at time of lower load.

Factory automation involves wireless communications for data acquisition from devices and sensors as well as messaging for device control and actuations. Wireless devices can easily be located at key positions at low cost and without wiring. Industry applications require however the communication system to provide a certain degree of predictability and reliability to assure that processes operate as intended. Some applications have hard real-time requirements on the communication, e.g., those involved in automatic control loops, and may hence need wired connectivity or wireless solutions that offer certain degrees of guarantees such as IEEE 802.15.4 with WiressHART [37]. Other applications accept softer assurances on predictability and reliability and are thereby candidates for wireless IEEE 802.15.4 with CSMA/CA installation and proportional differentiation.

Applications that can manage with softer assurances include time-constrained device control and actuations as well as collection lower volumes of time-critical data. Such data may originate from observations generating larger amounts of data but are then pre-processed by sensor devices to detect urgent matters such as malfunction and critical wear. Thereby, sensor devices can perform accurate monitoring although connected via constrained wireless networks such as IEEE 802.15.4 [4].

3.2 Load control in collision detect networks

Wireless networks based on collision detection (i.e., CSMA/CA) rely on that competing sources not too often try to use the channel in the same time slots. Collisions occur when sources in dense networks transmit simultaneously, which result in lost data and lower overall throughput [38].

With 802.15.4 CSMA/CA sources perform a Clear Channel Assessment (CCA) before transmission to avoid collisions. However, when several nodes perform CCA at the same time, more than one of those nodes may detect the channel as free and transmit simultaneously. Alternatively, all sources may detect the channel as busy, which means that none of them will transmit with reduced network utilization as result.

CCA fails more frequently as load increases resulting in collisions and packet loss or in that no packets are being sent. This explains why load control in certain situations can reduce the amount of failed CCAs and thereby improve throughput in 802.15.4 CSMA/CA networks. Load control further reduces delay caused by retransmissions of lost data as well as queuing delay at the MAC layer. Also, fewer packets are lost due to collisions and queue overflow.

3.3 Proportional differentiation and load control

Proportional differentiation has been considered in the context of the IETF differentiated services [39]. The assured forwarding (AF) per-hop behavior (PHB) group defines a drop precedence of a packet that determines its relative importance compared to other packets [40]. In case of congestion, forwarding nodes try to protect packets with lower drop precedences from being lost by preferably discarding packets with a higher drop precedence value. This means that within the AF PHB group, the forwarding assurance of a packet depends on drop precedence and the relation between available forwarding capacity and load. While this service model may be unpredictable in the public Internet with its variable and uncontrollable load, it is more suitable in controlled environments such as industry networks where load can be controlled.

Constrained wireless industry networks face varying capacity due to changing radio conditions and moving object impacting on transmission quality. This makes it hard to offer strict assurances on forwarding capacity to more than a small fraction of all traffic. With a more relaxed service model aiming at proportionally distributing forwarding capacity to wireless devices based on stated demands, available capacity is more efficiently used.

We define a service model that allows for pairing load control with needs for predictability to offer high utilization of wireless channels, low delay, and demand-based distribution of available forwarding capacity. Demands are expressed for each node using a common network resource as fractions of the total available forwarding capacity. By monitoring this capacity, made as stable as possible through load control, each node obtains predictable and reliable throughput with low delay. The delay is not proportionally differentiated but kept low though load control that keeps queues and back-off times short and limits the number of retransmissions.

4 Load control for proportional differentiation

This section defines our CLC. It was firstly defined in [36]. We herein further explain and motivate the preferred configuration for proportional throughput differentiation. With proper configuration, CLC also limits the channel load for high overall throughput and low delay.

4.1 System overview

The CLC iteratively adapts application data rates of all nodes using the same channel, e.g., an 802.15.4 CSMA/CA channel. This means that nodes implement rate control for their applications. That is, data rates are limited before queuing for transmission at the MAC layer.

Iterations consist of a measurement period in which perceived throughputs and loss rates are observed. These values are cognitively processed and matched to stated demands for forwarding capacity of each individual node. Utility functions are used for this processing to assess the quality in terms of application usefulness. The found utilities are matched with stated demands though fuzzy logic. The outcome from processing utilities and demand changes to the data rates of each node, increase or decrease. Transmission rates are adapted until no further changes to these rates are issued by the fuzzy logic, i.e., the load adaptation is finished.

The demands are expressed as fractions of the total capacity of the channel in question. This means that the obtained data rates vary with the capacity, which follows the herein made definition of proportional differentiation.

4.2 Measuring perceived quality

The CLC periodically collects the quality perceived by each transmitting node. Throughput and loss rates at the application layer of each node are used to decide based on the demand for transmission capacity and the proper sending rates of nodes to avoid overload. Nodes are assumed to respect their respective allowed sending rate. The sending rates impact the perceived quality and thereby the decisions for next period, whereby the proper load is iteratively found. It is defined as a centralized unit for the simulation-based evaluation. Later in this paper, we discuss however implementation alternatives such as locating the controller in a gateway node with permanent power and likely to have sufficient processing capabilities and memory.

The CLC tracks packet loss rate and throughput obtained by each individual node over a pre-defined measurement period. Packets issued for transmission during the measurement period only are considered when calculating loss rates and throughput. That is, packets already in queue for transmission when the measurement period starts are excluded from loss and throughput calculations. This means that overload resulting in queuing is detected as high loss rates although packets may not be actually dropped. The CLC tracks and controls hence delay although not directly measured.

4.3 Utility functions

When throughputs and loss rates are obtained, the CLC transforms them via utility functions to assess the quality of transmissions in terms of application usefulness. The utility functions combine these two variables into a single utility value to be used as input to the fuzzy logic. The formulas of these utility functions were defined based on controlled experiments for different network scenarios [41].

Equation 1 was introduced in [42]. It defines the logarithmic function receiving two parameters, the throughput t measured at the receiver, and the maximum throughput $R_{\max}$ for the flow. The two constant values $b1$ and $b2$ define the offsets.

$$u_t{}^{(n,i)} = 100\frac{\log_{10}(\min(t, R_{\max}) + b_1) - b_2}{\log_{10}(R_{\max} + b_1) - b_2} \qquad (1)$$

Figure 1 presents the utility $u_t{}^{(n,i)}$ from throughput at the application layer. The constants define the shape of the curves. The profile of curve with $b2 = 5.7$ giving a close to linear relation between throughput and utility was selected for evaluation. This choice is motivated by that it supports proportional differentiation of throughput better than a non-linear relation obtained with smaller values of $b2$. Such relation would give lower demand nodes more throughputs on the expense of nodes with higher demands.

Equation 2, capturing loss rate, was first presented in [43]. It includes three constants $b1$, $b2$, and $b3$ and β defining the steepness. With this function, the utility decreases logarithmically with the increasing loss rate p. The curve with $b1 = 250$ was chosen for evaluation, the lowest line in Fig. 2. This choice was made to strongly feedback queue

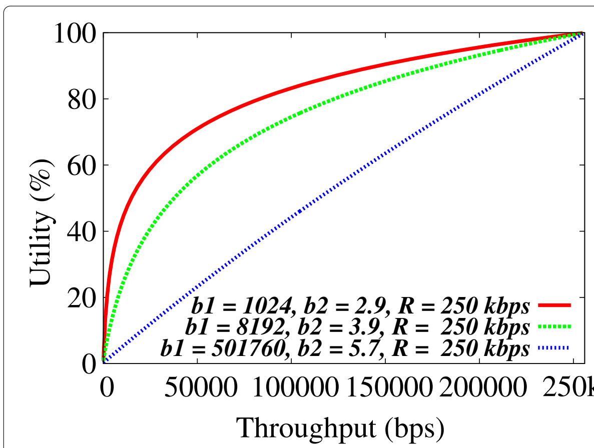

Fig. 1 The utility function of throughput. The figure shows the utility function for throughput at application layer/middleware

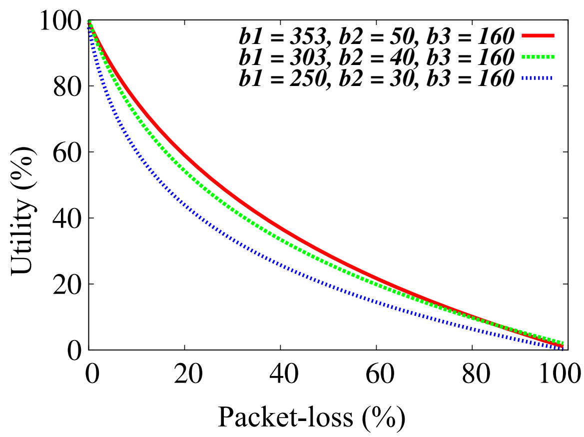

Fig. 2 The utility function of packet loss. The figure shows the utility function for packet loss at application layer/middleware

build-up and loss to the CLC aiming at usable capacity with low delay and loss.

$$u_p{}^{(n,i)} = b_1 + b_2 ln(b_3 + \beta p) \quad (2)$$

The two utility functions for throughput and loss rate respectively are added together with different weights, (Eq. 3). This gives a single utility $u_c{}^{(n,i)}$ for decisions on rate adaptations.

$$u_c{}^{(n,i)} = 0.6u_p{}^{(n,i)} + 0.4u_t{}^{(n,i)} \quad (3)$$

4.4 Fuzzy logic

The fuzzy logic of the CLC matches utilities $u_c{}^{(n,i)}$ of the past measurement period with stated demand of each node, that is, two inputs and one output for each node and 24 values in and 12 out for 12 nodes. The fuzzy logic includes four blocks: Fuzzifier, Inference Engine, Fuzzy Rule Base, and Defuzzifier (Fig. 3).

After fuzzification, the variables are processed in the Inference Engine, which uses the rules from the Fuzzy Rule Base, Table 1. They describe the correlation between the two inputs and one output for each node. The following terms are assigned to the outputs describing how to adapt the data rate: Decrease Quick (DQ), Decrease Medium (DM), Decrease Small (DS), Increase Small (IS), Increase Medium (IM), Increase Quick (IQ), and STABLE.

For each R_j rule where $1 \leq j \leq N$ and N is the number of rules, Eq. 4 describes the relation between outputs and inputs. Two inputs x and y are translated into fuzzy values of A_j and B_j. The *IF-THEN* relation returns the z output value for C_j linguistic value.

Table 1 Table of rules for fuzzy logic

	Utility			
Demand	Tiny	Small	Medium	Big
Small	DQ	DQ	IS	STABLE
Medium	DQ	DM	IM	STABLE
Big	DM	DS	IQ	STABLE

$$R_j \text{ IF } x \text{ is } A_j \text{ AND } y \text{ is } B_j, \text{ THEN } z \text{ is } C_j \quad (4)$$

The fuzzy relation is represented by Eq. 5, where the logic operators are used ∩ for *AND*, ∪ for *OR*, and x for *THEN*.

$$\begin{aligned} R &= [(A_1) \cap B_1)\mathrm{x}C_1] \cup \ldots \cup [(A_2) \cap B_2)\mathrm{x}C_2] \\ &= \cup_{j=1}^{N} \left[(A_j) \cap B_j)\mathrm{x}C_j\right] \end{aligned} \quad (5)$$

From Eq. 5, we obtain Eq. 6 for *C(z)*.

$$C(z) = R\,(x_0, y_0, z) \quad (6)$$

To convert input values into output values, we implemented the defuzzification method named Mean of Maxima (MOM) [44], pages 206-207. Firstly, the minimum and maximum values are selected from all inputs for each rule. Using Eqs. 5 and 4 where ∧ means minimum and *OR* symbols are converted to maximum operations, we result in Eq. 7.

$$C(z) = max_{1 \leq j \leq N} \left[A_j\,(x_0) \wedge B_j\,(y_0) \wedge C_j(z)\right] \quad (7)$$

For each maximized point $z_1 + z_2 + \ldots + z_p$ of *C(z)*, one output value of *MOM[C(z)]* is calculated (Eq. 8), i.e., the data rate adapting value for each transmitting node.

$$MOM[\,C(z)] = \frac{z_1 + z_2 + \ldots + z_p}{p} \quad (8)$$

Figure 4 shows how the CLC adapts the load by changing data rates based on demand and utility. That is, the steer rate is the fraction of change to previous data rates.

5 Evaluation through simulations

We illustrate the operation of the CLC through simulations. This is to show the adaptive behavior of the CLC and to examine its basic properties with respect to

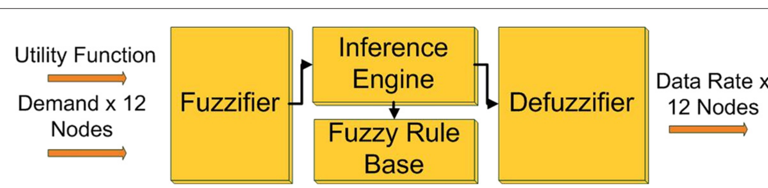

Fig. 3 The fuzzy logic model. The figure depicts the blocks of the fuzzy logic controller

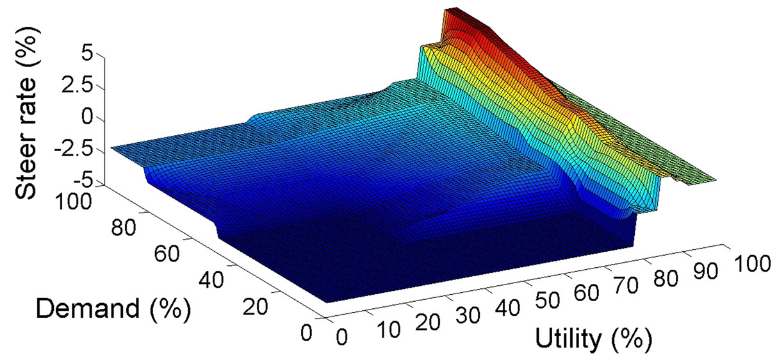

Fig. 4 Three-dimensional model of fuzzy logic for steering a data rate. The figure gives a three-dimensional view of the fuzzy logic behavior

throughput efficiency, adaptation rate, and predictability related to differentiation.

5.1 Simulation setup

A single-channel network with one sink node and 12 transmitting nodes was set up in NS-3 [4]. Nodes transmit with 2.4 Ghz parameters; bandwidth (maximum 250 kbps), payload (80 Bytes), transmit power (+3.0 dBm), energy detection threshold (−96 dBm), CCA energy threshold (−99 dBm) and with CSMA/CA and in ad hoc mode (Fig. 5). Sensors and actuator devices are normally limited in their capacity to process and transmit data. This means that a single sensor may not fully utilize the capacity of 802.15.4. For our evaluation, we assume that nodes are capable of transmitting at 65 kbps at most.

5.2 Overall throughput and loss rate

The overall throughput and loss rate with and without CLC was examined over a wide span of loads, starting from 65 kbps and increasing in steps of 65 kbps towards heavy overload, about three times the maximum capacity of 250 kbps. Without CLC, load was increased by incrementing the number of nodes sending at full speed, 65 kbps, and by increasing the total load of all source nodes in steps of 65 kbps, respectively. In the latter case, transmission rates were randomly distributed among the 12 sending nodes. With CLC, the total demand was increased in the same manner, for all nodes in steps of 65 kbps. Resulting throughput and loss rate with CLC was observed after that no further changes to transmission rates are issued by the fuzzy logic. A measurement period of 10 s was used by the CLC. Simulations were repeated 20 times for mean values with confidence intervals.

Figure 6 shows the expected decrease without CLC as the channel becomes gradually more saturated, when the load exceeds the channel capacity of 250 kbps. Best throughput is observed at a load of 195 kbps, which the CLC manages to keep also for considerably higher total demand. Loss rates are further kept very low with CLC, while they grow large without this load control (Fig. 7). Moreover, as can be seen in Fig. 8, the queue occupancy

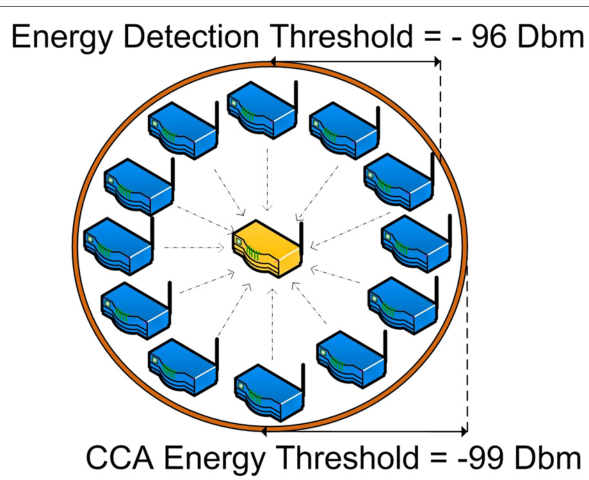

Fig. 5 Dense area of the wireless nodes. The figure illustrates a WSN with all nodes within transmission range

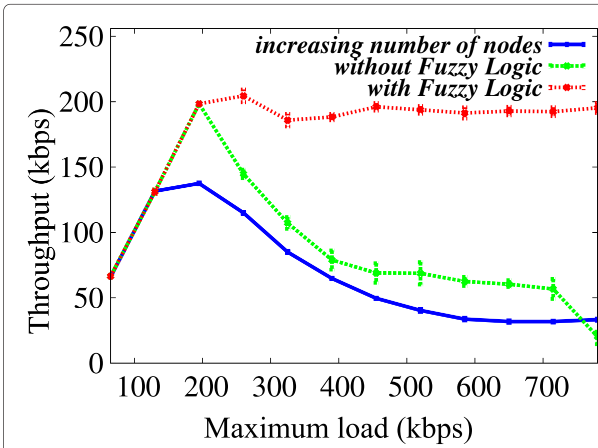

Fig. 6 Total channel throughput as a function of increasing load. The figure shows throughput with CLC and without at different loads

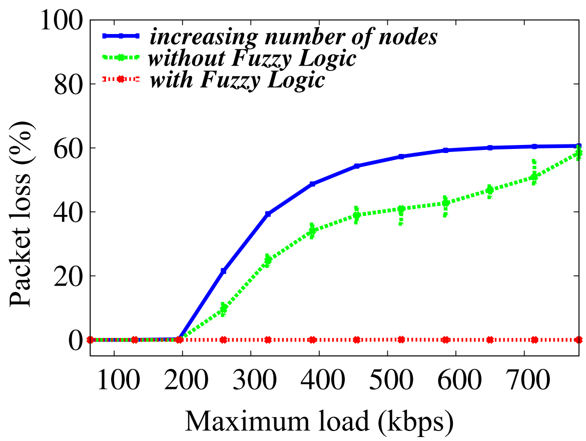

Fig. 7 Loss rate due to full queue as a function of increasing load. The figure shows loss rates with CLC and without at different loads

and hence the queuing delay is very low with CLC while growing high with load when no load control is applied.

5.3 Adaptation time and obtained capacity

The adaptation time was evaluated for different values of the measurement period and buffer available for queuing. Shorter measurement period results in less time needed for adaptation unless the number of iteration steps needed to finish the adaptation increases too much.

Figure 9 shows the mean number of iterations from 10 independent simulations for different measurement periods and buffer space (i.e., maximum queue lengths). For larger buffers and shorter periods, results are stable around nine iterations, while they grow larger for small buffers and longer periods, especially for measurement periods of 7 and 10 s. With buffers of 20 packets and with measurement periods of 4, 7, and 10 s, the CLC reaches a maximum of 151 iterations without finishing the load adaptation.

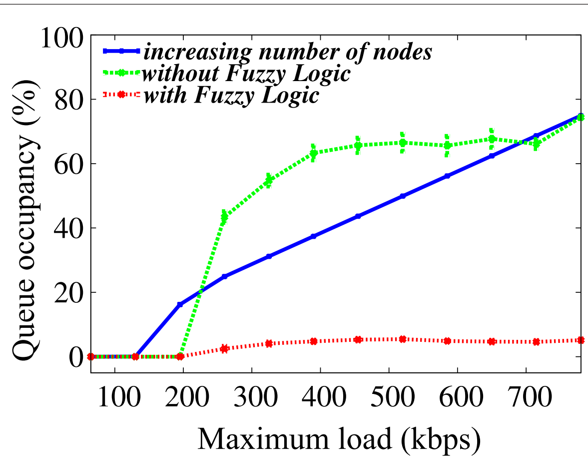

Fig. 8 Queue occupancy as a function of increasing load. The figure shows queue occupancy with CLC and without at different loads

Figure 10 shows the number of iterations translated into time. This graph illustrates that shorter measurement periods are preferable and indicates that too little buffer space for queuing may cause longer adaptation times. At best, the CLC manages to adapt in around 9 s. This can prove useful when urgent matters such as malfunction or critical wear are detected and forwarding capacity need to be redirected to devices close to the problem in question.

Although short measurement periods are preferable to obtain quick load adaptation, Fig. 11 shows that throughput suffers slightly from short periods but gain a little from smaller buffers. The differences are however generally small, especially between configurations not generating packet loss (Fig. 12). For these configurations, throughputs are in the range between 159 and 179 kbps, with generally higher values for longer measurement periods. Nevertheless, longer load adaptation times can be traded for higher throughput.

5.4 Proportional differentiation and delay

Figure 13 shows average differences between stated demands for forwarding capacity and obtained throughputs. For example, in case the stated demand is 10 % of the total capacity for a node that obtains 8 % of the overall throughput, the data rate error is 2 %. For shorter measurement periods, these errors approach 3 % and are generally higher than for longer periods. Better performance in terms of lower data rate errors can hence be achieved at the price of longer load adaptation times.

With 12 nodes sharing around 168 kbps, each node gets only 14 kbps in average and some less with different demands for forwarding capacity. Hence, with 80 Byte packets (640 bits), each packet needs about 0.05 s to be transmitted. Figure 14 shows generally very low queuing, less than one packet in average for shorter measurement periods. The queuing grows however with longer measurement periods and shorter maximum queue lengths, peaking 16.4 queued packets in average and about 750 ms in queueing delay for 7 s measurement period and maximal queue length of 40 packets. At overload and without load control, the average queue occupancy can grow large enough to cause several seconds of delay, which may be very unfortunate for mission-critical messaging in industrial automation systems.

6 Implementation aspects and considerations

For a mechanism like CLC aimed for constrained networks, it is essential that the mechanism allows for efficient and low-overhead implementation. Assuming that the CLC is implemented in a central node, e.g., a gateway between a WSN and the Internet, it is important that the variables communicated with each node come

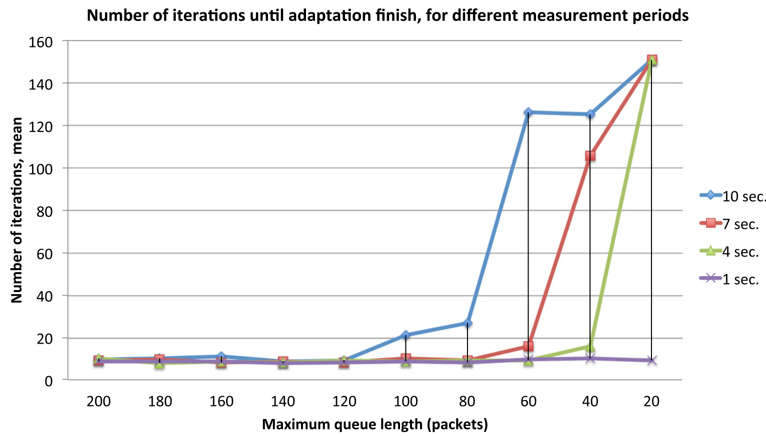

Fig. 9 Number of iterations until load adaptation finish. The figure shows the number of iterations until load adaptation finish for different maximal queue lengths and measurement periods

at low overhead and are efficiently transported over the constrained WSN.

6.1 Updating variables for assessing perceived quality

As defined in this paper, the CLC relies on periodic measurements of per-node throughput and loss rate. These measurements should not burden constrained wireless devices and instead be processed to largest extent possible by nodes having permanent power supply and enough computational capabilities and memory. In wireless sensor and actuator networks for industry automation, gateway nodes that interconnect these wireless devices into a system for knowledge-based factory automation can be expected to meet these criteria.

For deployments where the gateway node has sufficient processing power, constrained wireless nodes can be relaxed by the use of sequence numbers for transmitted packets. CLC will then run on the gateway node, which communicates changes to allowed data rates to the wireless nodes as well as for its own transmission over the wireless channel. When communicating these changes, the gateway node also offsets the sequence number of each node so that it knows which packets are issued before and after the change, respectively. For example, for each node, it may offset the sequence numbers with a value power of two higher than the last seen packet that arrived. Such an offset can be efficiently implemented using bit shift by the wireless nodes and will hence impose minimal overhead to these constrained devices.

The offsetting of sequence numbers allows the gateway node to simply count received packets issued after the change and detect losses from the sequence numbers. Throughput and loss rates are thereby measured by the gateway without other involvement of wireless nodes but receiving messages for rate changes, rate limiting, and sequence number offsetting. Rate limiting to 10ths of

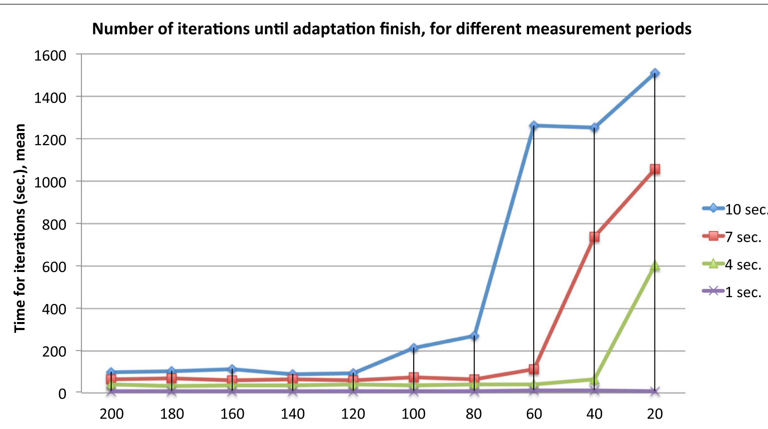

Fig. 10 Time of iterations until load adaptation finish. The figure shows the times until load adaptation finish for different maximal queue lengths and measurement periods

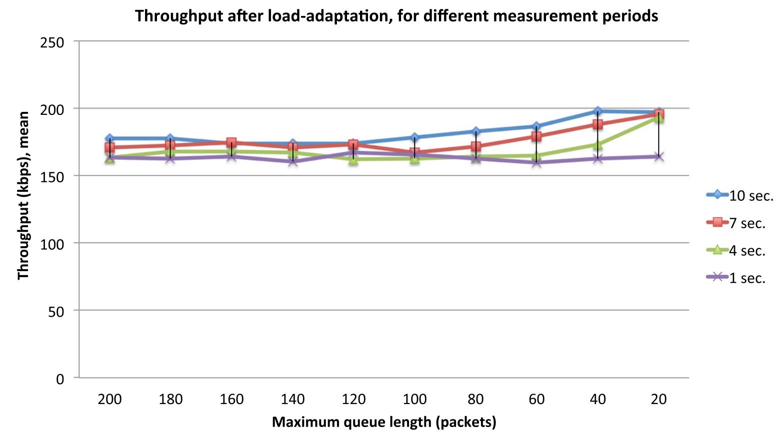

Fig. 11 Throughputs after load adaptation. The figure shows the resulting throughput after load adaptation finish for different maximal queue lengths and measurement periods

packets per second is generally well achievable through interruptions also at low performance microcontrollers.

Should several gateways be deployed for the same channel, they should be capable of selecting a single node for the CLC. Measured throughputs and loss rates as well as rate changes can then be communicated over wired connections.

6.2 Transport of data for load control

Constrained wireless devices for industrial automation may implement the Constrained Application Protocol (CoAP) [21]. CoAP provides request/response interaction with applications for industrial automation and other machine-to-machine (m2m) applications. It is designed for easily interfacing with HTTP for integration with Web-based systems on the Internet.

For devices already implementing CoAP for control of measurements and actuations, this protocol can be used also to operate the CLC. That is, offsetting the sequence number status and changing the data rate for a device at a CLC iteration can be done with a simple CoAP PUT method message. Without CoAP, similar solutions are possible, e.g., by issuing remote procedure calls over UDP to set those values.

7 Future work

The herein presented approach of a proportionally rate-differentiated service related to load control for WSNs deserves further studies in several possible directions. Such further work can be categorized into the following areas of future research on this approach for differentiated forwarding in WSNs; (1) proportional differentiation

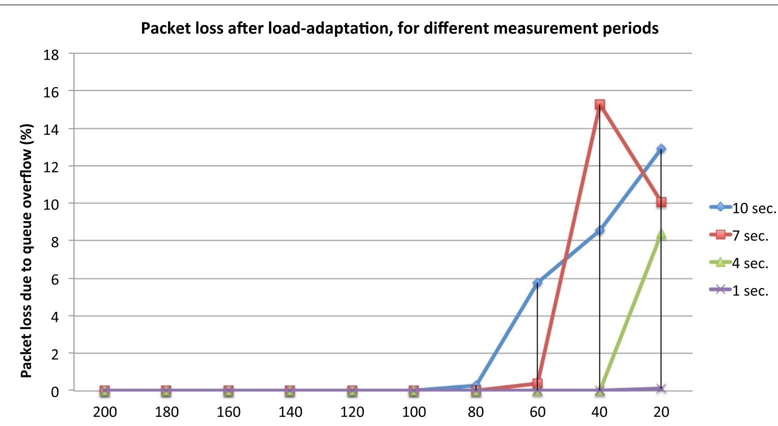

Fig. 12 Packet loss rates after load adaptation. The figure shows the resulting loss rates after load adaptation finish for different maximal queue lengths and measurement periods

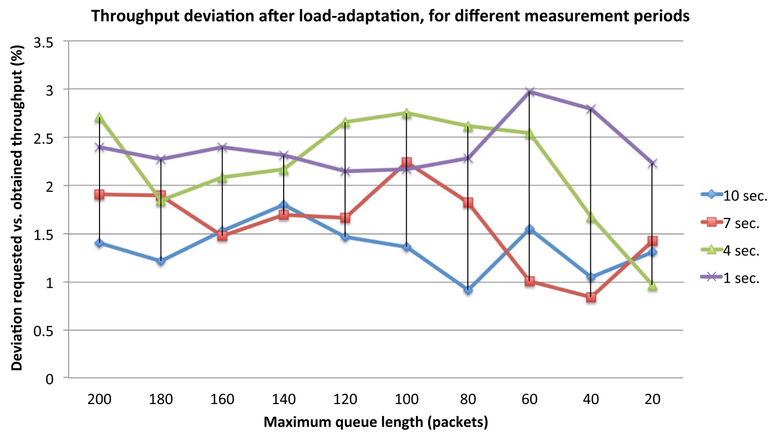

Fig. 13 Differences and demanded and obtained throughput. The figure shows how close to demanded throughputs the system delivers, for different maximum queue lengths and measurement periods

in multi-hop WSNs and (2) alternative mechanisms for proportional differentiation in WSNs.

7.1 Proportional differentiation in multi-hop WSNs

Multi-hop WSNs is of particular interesting for further work since multi-hop scenarios may involve greater uncertainty on available forwarding capacity over potentially time-varying topologies and communication quality [45]. Furthermore, in such scenarios, the main part of the end-to-end (e2e) delay appears in transmissions and due to contention and queuing [46]. Contention and queuing in CSMA/CA relates directly to network load in terms of the frequency of simultaneous transmission attempts from different nodes in range of each other. As shown in this paper, by controlling the load of simultaneously transmitting nodes when contention occurs, the network throughput can be improved (Fig. 6) and queuing delay decreased (Fig. 7).

The effect of load control on network throughput and delay in multi-hop scenarios is likely to depend on deployment strategies for WSN coverage and connectivity [45]. For example, in barrier coverage scenarios, sensors are deployed to detect any moving path crossing a belt region. Such deployment typically creates a chain-like topology, while blanket coverage scenario aiming having a sensor node in every point of a field, the deployment typically becomes dense with many possible paths across the WSN. Different types of network coverage and connectivity should be considered in considering load control and proportional throughput differentiation for multi-hop WSNs.

Wireless sensors are most often battery operated. Consequently, careful energy management and use is of outmost importance to ensure long enough lifetimes of wireless sensor systems. Sleep scheduling [47], data aggregation schemes with compressed sensing (CS) [48, 49],

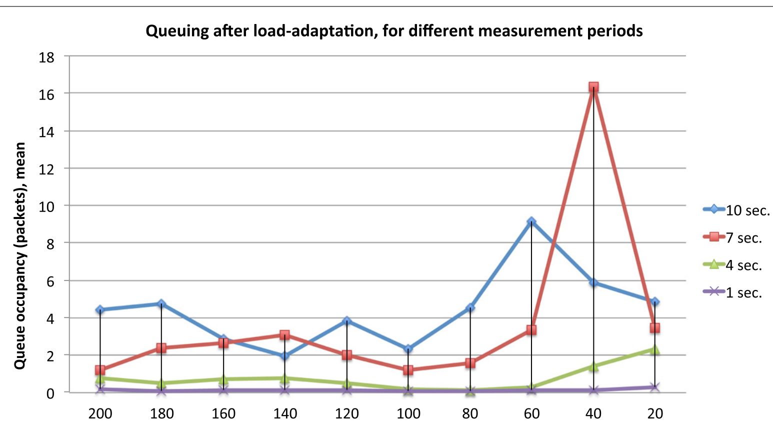

Fig. 14 Delay from queuing before transmission. The figure shows the resulting queuing in amount of packets after adaptation finish, for different maximum queue lengths and measurement periods

enhanced routing [50], and topology control by adapting transmission power [46] are well-explored means to efficiently use available energy. Moreover, the concept of content-centric networking facilitates named based routing of requests for data and in-network caching of content, which can reduce the amount of traffic needed to serve consumers of the data [51].

Sleep scheduling, also known as duty cycling (DC), has been identified as an important technique for energy conservation in WSNs [5]. DC allows wireless sensor nodes to turn their radio on and off to conserve energy, which can cause varying network topology and load. Hence, further studies on load control for low delay and efficient capacity use with proportional throughput differentiation in multi-hop WSNs should consider sleep scheduling of nodes. Algorithms for DC can be categorized into five types of communication modes, i.e., unicast, anycast, broadcast, multicast, and coveragecast [47].

Coveragecast is a common communication mode in WSNs with many sensors producing data for one or a few collecting sinks. This communication pattern creates star topologies in which DC has a clear impact on e2e delay. It can be combined with data aggregation schemes that let intermediate nodes combine received data with their own to reduce the amount of data to be transported over the e2e WSN path. Data aggregation can further be combined with CS techniques introducing in-network processing of the aggregated data and enhanced routing to further reduce the amount of communicated data as well as the total energy consumed in the network.

Given the common situation of energy scarcity in WSNs, energy harvesting constitutes an important part of many sensor systems. In [52], Afzal et al. presents a unified perspective that addresses energy efficiency and harvesting together with cognitive radio (CR) techniques for dynamic spectrum access (DSA) for more efficient use of available radio spectrum. Mobile cloud computing technologies is also included in their proposed architecture incorporating a cognitive Internet of Things (IoT) engine that interacts with a cloud-based engine for reconfiguration, inference, learning, and orientation. A new performance metric called the overall link success probability is introduced to capture both energy and spectrum efficiency constrains.

Should proportional differentiated service models be further considered for multi-hop WSNs, collective metrics such as the overall link success probability may be needed to allow for good overall network performance in the presence of differentiation. Proportional differentiation models bring benefits of allowing for cognitive approaches, e.g., to balance energy and spectrum efficiency constrains while offering differentiation between nodes or streams of data. Stricter differentiation models offering stronger assurances or even guarantees are likely to impact more on performance metrics related to energy and spectrum efficiency. For example, to guarantee a certain throughput at low delay, excessive transmission power may be needed, which can reduce the overall network performance.

Clearly, several interacting techniques can be used to improve the overall multi-hop WSN performance in terms of energy and spectrum efficiency, energy consumption and sensor system lifetime, communication delay, overall throughput, and reliability and predictability in capacity allocations. We believe that load control with proportional throughput differentiation can contribute to improving these quality metrics. A mechanism like the CLC needs to be integrated with other techniques to come to its best. Also, the potential negative impact from the proportional differentiation on overall network performance should be analyzed and quantified in relation to the fundamental performance limits of the medium access control (MAC) protocol in question.

Upper bounds on network utilization for any MAC protocol and for fixed linear and grid topologies are defined and proven by Xiao et al. in [53]. They aim at extending their results for other topologies such as deployments where both sides of a sink node can have sensor nodes and the larger communication ranges but two-hop or more neighbors can hear messages. Thereby, these upper bounds may hold also for the coveragecast communication modes, which we believe is of fundamental importance for the type of industrial applications through of in this paper.

7.2 Alternative mechanisms for proportional differentiation in WSNs

As shown in Section 5.3, short measurement periods for quick load adaptation results in slightly less overall throughput, i.e., reduced overall network performance. Although smaller buffers improve the network performance, short measurement periods still typically come with reduced throughput. Faster load adaptation resulting in both high overall network performance and targeted proportional throughput differentiation may be possible by using information below the socket interface. In particular, information on the queuing delay that appears at the MAC layer would provide a quicker feedback on contention and overload than changes in detected throughput and loss at the application layer.

8 Conclusions

Wireless connectivity is attractive for industrial automation when low cost deployment is desired and in harsh environments where wiring is difficult, costly, and may easily get damaged. Predictable throughput and delay is important for industrial wireless communications. This paper defines and motivates demand-based proportional differentiation of forwarding capacity with low loss rates and delay. For wireless networks such as 802.15.4 with CSMA/CA, such differentiation can be implemented through cognitive load control.

We show through NS-3 simulations that a cognitive load controller (CLC) can differentiate the forwarding service given to individual devices based on stated demands for capacity. The CLC further offers high utilization and low loss rates and delay. When changing the distribution of demands between devices, the CLC is shown to adapt the proportional differentiation in reasonable time, down to around 10 s and less than a minute. It offers slightly higher overall throughput and more precise differentiation when configured for longer adaptation time.

The CLC can be implemented without burdening constrained wireless devices, which makes demand-based proportional throughput differentiation a tractable choice for wireless communications in industrial automation.

Competing interests

The authors declare that they have no competing interests.

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