

Measurement and Prediction of Central/Peripheral Network Properties based on Regression Analysis

A Parametric Foundation for Performance Self-Management in WSNs

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Abstract—Predicting performance-related behavior of the underlying network structure becomes more and more indispensable in terms of the aspired application outcome quality. However, the reliable forecast of QoS metrics like packet transfer delay in wireless network systems is still a challenging task. Even though existing approaches are technically capable of determining such network properties under certain assumptions, they mostly abstract away from primal aspects that inherently have an essential impact on temporal network performance dynamics. Also, they usually require auxiliary resources to be implemented and deployed along with the actual network components. In the course of developing a lightweight measurement-based alternative for the self-inspection and prediction of volatile performance characteristics in environments of any kind, we selectively investigate the duration of message delivery and packet loss rate against various parameters peculiar to common radio network technologies like *Wireless Sensor Networks (WSNs)*. Our hands-on experiments reveal the relations between the oftentimes underestimated medium access delay and a variety of main influencing factors including packet size, backoff period, and number of neighbor nodes contending for the communication medium. A closed formulation of selected weighted drivers facilitates the average-case prediction of inter-node packet transfer delays for arbitrary configurations of given network parameters even on resource-scarce WSN devices. We validate our prediction method against basic multi-hop networking scenarios. Yield field test results proof the basic feasibility and high precision of our approach to network property estimation in virtue of self-governed local measurements and regression-based calculations paving the way for a prospective self-management of network properties based upon autonomous distributed coordination.

Index Terms—Wireless Sensor Networks, Experimentation, Performance, Prediction, Measurements, Regression Analysis

I. INTRODUCTION

Latest achievements in semi-conductor technology and *micro-electro-mechanical systems (MEMS)* have facilitated an increasing demand for low-cost sensor devices that are miniaturized in shape but efficient in operation. Further advances in the development of wireless communication techniques and network equipment have made WSNs emerge as the seminal service platform for realizing various valuable applications of today and the ambitious vision of *Ambient Intelligence (AI)* of tomorrow [1], [2]. At this stage, their small size and long life-span make WSN nodes suitable for many application

domains where dense sensing close to physical phenomena as well as large-scale collection and exchange of data is needed. Typically human-administered workaday applications include biodiversity monitoring, emergency treatment support, facility management, medical diagnostics and home automation [3], [4]. In turn, the future design of AI envisions administration-free deployments of even smaller, poly-functional and possibly also heterogeneous devices gathering, processing and exchanging information from different sources of the environment in order to exert influence on physical processes in a further step. The involved ability of autonomous interaction with ambient phenomena rather than with humans in the first place is believed to be the crucial step towards pervasive environmental control. However, in the long term, the implicated features are not conceivable without a common notion of autonomy in regard to a self-governed management of not only explicitly adjustable technical parameters but also implicitly controllable functional properties as encountered in actual hardware/software network deployments. At the same time, the reliable and precise estimation of performance metrics without human intervention constitutes a crucial feature of aspired applications installed in, especially but not limited to, highly dynamic environments, e.g., traffic control in over-crowded urban areas, rescue operations in unstable disaster zones, let alone indoor surroundings with divers mutually affecting home and facility instruments established for automation purposes. From the point of view of various research endeavors, it is obviously challenging to bring these stringent requirements in line with present-day equipment that essentially requires manual superintendence in order to fulfill any task at all due to lacking learning and adaptation mechanisms [5], [6]. However, just as much as the concept of pervasive computing embodied by ad hoc WSNs has enthused academia as well as the industry, the notion of autonomic computing has witnessed great attention in regard to the self-management of complex computer systems [7], [8]. Autonomic networking that builds upon the same principles within the context of the networking domain in order to tackle the increasing complexity of ever-growing distributed (wireless) network systems, has always played an important role to the same degree [9], [10]. Whereas measurement-based estimation of metrics bears good prospects

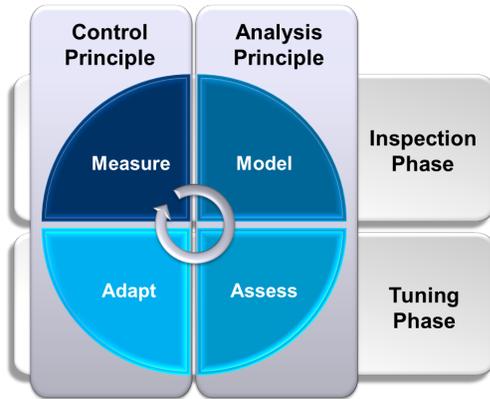


Fig. 1: Performance Self-Management Task Cycle

in general [11], [12], its consideration within the context of autonomic self-management constitutes an even more promising approach. However, the estimation of performance metrics in multi-hop networks like WSNs is not a straight-forward task even for approved methodologies [13], [14]. Furthermore, many works inherently rely on the inclusion of auxiliary computing resources to tackle the implied issues of management due to their common intricacy. However, we believe naturally autonomous systems, as WSNs are aspired to become, shall only rely on their own resources to fulfill their tasks all by themselves. Only this way renders them useful for any kind of dynamic situations where additional computing resources are just not available or integrable. That is why we follow the approach to enable any given WSN to make use of what it is being provided with, the enabling investigations of which are the essential part our long-term research endeavors and to some extent also part of this work.

On this note, the remainder of this work is organized as follows. In Section II we introduce our approach to the self-management of performance properties including the needed terminology as the basis for our investigations. Section III deals with details on our experimentation methodology for the evaluation of network parameter impacts on major network properties including a subsequent result analysis. As part of Section IV, we discuss the proposed performance prediction technique, review its general quality and also validate the results yield before against a multi-hop scenario. Concluding remarks and prospects on future works are eventually provided in Section V.

II. PERFORMANCE SELF-MANAGEMENT IN WSNs - PARAMETERS, PROPERTIES AND METRICS

In general, the costs and benefits of autonomic networking not only depend on the circumstances the corresponding hardware is subject to but also on the correct handling of network (protocol) parameters and the appropriate interpretation of encountered performance characteristics. Since this inherently requires an efficient management of available and controllable resources, it suggests itself to introduce a comprehensive self-ability concept we recognize as *Performance Self-Management (PSM)*.

In contrast, however also in complement, to other works that primarily approach network autonomy by trying to establish overlay-like infrastructures that are either attached to or even pervade the network of interest, we take the approach of investigating principle methods that enable node-local self-abilities, as we call them, from the node-local perspective first. Nonetheless, we also share the view that during a transitional period it will be required to provide the network entities with feedback and functional support until all those methods fuse in a collaborative manner rendering such networks operable on a fully autonomic basis. That is why, we basically distinguish intrinsic from extrinsic PSM in that we separate WSNs where most of the basic features are self-governed, yet still require assistance from other entities for maintenance reasons, e.g., human administrator during run-time operation, and WSNs that keep-up the desired performance aspects on their own from the start of the network application deployment until the end of its life-time.

In this spirit, we coin the term of *Intrinsic/Extrinsic Performance Self-Management (I/EPsm)* so as to define the scope of our research directions within the context of wireless networked systems like WSNs. To this end, we also identify a set of sub-routines that need to be implemented on any I/EPsm-enabled node as part of that concept. These modular self-abilities include measurement, modeling, assessment and adaptation. The so-called *I/EPsm Task Cycle* unites the four cornerstones of our approach the accomplishment of which is based upon two fundamental principles that saturate two recurring phases as illustrated in Figure 1 and outlined in the following.

Inspection Phase: The measurement task includes the inquiry of relevant parameter values along with the capture of performance-related statistics for the network properties of interest as indicated by the requirements of the running application (*Control Principle*). The subsequent modeling task implies the identification of the best-fitting model type for each of the network properties in question as well as the instantiation of these models with the appropriate parameter values as determined beforehand (*Analysis Principle*).

Tuning Phase: The evaluation of the current performance quality against given application requirements and, as the case may be, the identification of those parameter constellations that need to and, essentially, that can be changed so as to adhere to imposed network property demands is part of the assessment task (*Analysis Principle*). At last, the agreed and optional adaption of the selected modifiable parameters at the corresponding entities is accomplished in view of the reinitialization and subsequent iteration of the overall mechanism (*Control Principle*).

With regard to the frequency of the task cycle procedure, conceivable solutions include time-based, entity-controlled and event-triggered approaches that will depend on the network system application and the aspired performance sustainment quality. Moreover, since the accomplishment of at least a subset of all these modular tasks imposes a higher computational as well as communicative burden on selected nodes involved

in execution, load-balancing mechanisms shall be applied for energy saving purposes as part of future considerations.

For the sake of transparent traceability of the upcoming details in the subsequent sections, a clear terminology of the objects of investigation is to be introduced next.

A. Terminology

In the context of I/EPSPM, our terminology incorporates the general distinction between two variable quantity types, network parameters and network properties, both of which become manifest in metrics, i.e., schemes of quantifiable measures for the characterization of given physical phenomena. However, whereas network **parameters** include any accessible settings that need to be directly or indirectly adjustable when acting as drivers for network property control, network **properties**, on their part, involve any attributes the values of which defy direct access and are obtainable merely by means of measurements and/or computations based on statistical/analytical inference in conjunction with concrete parameter values.

We further differentiate the viewpoint on parameters and properties from a central and a peripheral perspective. **Central parameters** refer to intra-node/node-local variables the values of which can be determined and tuned without any interaction with other entities (e.g., power amplifier level, packet size, backoff period, ...) while **peripheral parameters** encompass inter-node/network-wide system variables usually accessible and modifiable only by virtue of collaboration (e.g., number of active nodes in cluster, network topology, number of neighbor connections, ...). Analogously, **central properties** pertain to measurable or computable attributes that relate to the status of a single network node (e.g., medium access delay, in-system backlog, traffic arrival rate, ...) in contrast to **peripheral properties** which are concerned with attributes going beyond a single network entity up to network-wide conditions (e.g., end-to-end delay, cluster packet loss rate, network backlog, ...).

In some cases, otherwise regulable network parameters can be accessed but are immutable due to, e.g., management policies or might also need to be measured and somehow deduced from captured phenomena, respectively (e.g., channel frequency, node position, distance to neighbors, ...). However, as long as they remain uncontrollable to the involved network entity/entities, they are not considered drivers for any properties. Nonetheless, they may serve as invariable predictors for property value determination in the same manner as other measurable or calculable properties themselves can transitively do. Eventually, the causal relationship between given network attributes shall be subject to the inference of a suitable abstract intuition of real circumstances bound within a calculable construct, henceforth referred to as **performance model**.

As part of this work, we turn our attention to a representative selection of one peripheral and two central parameters to investigate their relation to two fundamental network properties as detailed in the following.

B. Network Properties under Investigation

In the work at hand we focus on two of the most prominent and also descriptive network properties capable of revealing the perception of what is known to affect the timeliness and disposability of data.

As per general convention the **End-to-End Delay (E2ED)** in packet-switched communication networks encompasses the entire time duration between the start of the sending process at the origin of the data of interest, commonly denoted as the source node, and the end of reception at the ultimate target referred to as the destination node [15], [16]. In between, several delay components, traditionally known as the processing, queuing, transmission, and propagation delay, can be identified dividing the E2ED into several time segments that deserve a more detailed contemplation in support of our forthcoming examinations.

- *Processing delay*: time to check received, treat backlogged and prepare to-send packet of interest primarily depending on amount of data to be processed
- *Queuing delay*: time packet is blocked from reaching destined communication port depending on current system/network load and data buffer size in the first place
- *Transmission delay*: time required to deliver entire packet onto communication medium particularly depending on size of data to be sent
- *Propagation delay*: time packet needs to traverse distance towards destination exclusively depending on signal propagation speed within given communication medium

While propagation delay is actually negligible in short-distance *Personal Area Networks (PANs)* like WSNs due to its marginal and usually constant impact on the overall time lag compared to the other delay components, queuing delay might become the largest driver for E2ED in store-and-forward networks that rely on data buffers. Yet, WSNs were originally not meant to emulate the behavior of networks with dedicated devices, such as highly buffered routers in IP-based nets, in order to solve fundamental networking issues like forwarding. They were intended make avail themselves of enabling concepts, e.g., data-centric collaboration, deployment redundancy and in-network processing rather than relying on single-node resources for such purposes [17]. According to this, a typical WSN node is endowed with a tiny transceiver buffer of only one packet per link direction [18]. Having said that, the illusive absence of queuing delay for small-buffered devices, ought not to be underrated especially when it comes to the packet loss and its implications on E2ED. In fact, a piece of data that does not reach its destination due to, e.g., network congestion might induce further delay by retransmissions as required by loss-intolerant network applications, not to mention the auxiliary timeout latencies introduced by the very usage of ACK-based reliable data transfer mechanisms [19].

With regard to the other two delay components, they are often assumed to be deterministically predictable solely by the knowledge of the hardware details, e.g., transmission speed of the radio transceiver, clock frequency of the microcon-

troller and the amount of data to be handled. However, this does not hold true for any functionality that is based on probabilistic procedures like the access arbitration in random-based shared-medium schemes as defined, e.g., in the IEEE 802.15.4 *Medium Access Control (MAC)* protocol for low-rate WPANs [20]. And, since the implicated delay for accessing the medium is usually regarded as part of the queuing delay, it is neglected in turn when abstracting away from queuing effects in buffer-scarce WSNs. Yet, regardless of which of the above components it is actually attributed to, it constitutes a remarkable influencing factor that necessitates a thorough elaboration and further clear terminological separation.

- **Packet Processing Delay (PPD)**: time for in-system preparation and passing of packet data through any layer of communication-related functionality from (when receiving) and towards (when sending) medium access controlling system module
- **Medium Access Delay (MAD)**: time spent on carrier sensing in conjunction with medium arbitration up to event of accessible idle medium based on underlying medium access mechanism
- **Packet Transmission Delay (PTD)**: time required to modulate entire packet onto communication medium up to the last bit of data
- **Packet Sending Delay (PSD)**: time to accomplish entire sending process, i.e., sum of PPD, MAD and PTD

In a sense, our terminology constitutes a more detailed extraction of the traditional division of delay components for practical reasons in view of the upcoming experimentation without loss of generality. That is to say, it allows to consider the otherwise peripheral notion of E2ED also from a central view of a single network entity. Indeed, a source node is prospectively supposed to predict the E2ED of a data packet to a single-hop destination as the sum of its locally determinable PSD and the PPD as encountered at the destination node. For the multi-hop destination case, the source node further adds the sum of the corresponding PPD and PSD for any other intermediate node the data packet needs to traverse. After all, only node-local knowledge about the constitution of its surroundings including inquired or deduced parameters and properties shall suffice to enable attribute prediction.

The **Packet Loss Rate (PLR)**, on the other hand, is yet another well-established network property that offers valuable clues to the current state of the peripheral as well as central view on performance. In a way, it can give significant feedback to network entities about the implications of current parameter settings on other network properties that it correlates with.

On this note, we define the PLR to be the number of packets that are not received at the destination node in relation to the number of packets issued at the sending source node. As a matter of fact, packet loss is hard to detect in network systems that renounce reliable data transfer mechanisms as commonly encountered in many broadcast-based WSN application scenarios. However, since the event of loss might be the consequence of a variety of reasons, e.g., system

failure, channel interference, duty cycling, that are implicitly interrelated to that metric, other properties or parameters might be consulted to deduce the PLR from the point of nodal view.

C. Network Parameters of the Evaluation Platform

Considering all major network parameters that are common to all wireless network technologies similar to the exemplary platform we evaluate in this work, we opt for one peripheral and two central parameters as the objects of investigation due to their most promising influence on the network properties mentioned above.

First and foremost, the total number of nodes constitutes an intuitive influencing factor for any kind of functionality, especially in case of WSNs that define their basic principles upon their numerical redundancy. However, since we are only interested in aspects from the central view of a single node, for the time being, we draw our attention to the neighbors in the vicinity of the node of interest that mutually contend for medium access the quantity of which shall be denoted as the **Number of Contenders (N_C)** from now on.

Secondly, the length of the data packets, henceforth the **Packet Size (P_S)**, containing application-specific payload as well as protocol-related management information that needs to be transferred from the source to the destination node is taken into account.

At last, we identify a central parameter with highest impact on the medium access behavior and, collaterally, also on the overall inter-node transport process, which is referred to as the **Backoff Period (B_P)**.

III. EXPERIMENTATION ON SELF-MEASUREMENTS - A CENTRAL/NODE-LOCAL APPROACH

As part of the control principle within the inspection-phase of the I/EPMSM task cycle, network nodes participating in network activity are supposed to capture any parameter values that are considered important with respect to their impact on certain network properties. To this end, we are particularly interested in all the performance-related information that can be obtained during regular network operation, i.e., collected or derived when sending, receiving or processing data in the context of orderly application execution (e.g., RSSI, medium access delay, traffic input, missing ACKs, ...) without the need for auxiliary energy consuming network communication.

According to this central/node-local approach, the subsequent experimentation deals with the basic feasibility of node-local measurements of network properties and adjustments of network parameters implemented on real-world WSN nodes leaning solely on out-of-the-box features as provided by the associated software/hardware platform. In this regard, we explore the dependency of PSD and PLR on three adjustable network parameters including B_P , P_S and N_C as specified in the previous section. Besides, in order to accommodate most WSN scenarios and also the situation of so-called “event showers” that are typical for many WSN applications, we designed our testbed environment and evaluation procedure correspondingly as detailed below.

A. Environmental Setup and Methodology

The evaluation platform used throughout the experiments is the notorious MICAz/TinyOS solution, one of the most commonly referenced WSN node implementations featuring high versatility in plenty of adjustable parameters and latest protocol mechanisms for the investigation of WSN applications. MICAz motes feature an 8 MHz microprocessor, 4 kB of RAM, 128 kB of code memory, and an IEEE 802.15.4-compliant transceiver for radio communication of 128 Byte packets with 250 kbit/s of maximum transmission rate [21]. As the standard operating system, TinyOS 2.1.2 based on the NesC programming language is applied for running the motes [22].

TinyOS implements a set of link-level primitives as specified by B-MAC including optional use of link-level ACKs, a duty cycling mode, and a basic CSMA mechanism without RTS/CTS that includes adjustable parameters for MAC. In the context of PSD measurements, these parameters play a fundamental role as delay-relevant factors. As per its carrier-sensing mode, after a first waiting time (initial backoff) each packet transmission attempt of a mote stipulates a prior *Clear Channel Assessment (CCA)* for channel state testing based on an averaged noise sampling mechanism [23]. If the CCA encounters a busy channel, the sending node backs off for a certain amount of time (congestion backoff). This backoff delay d_B is randomly drawn from an interval spanned by means of two parameters, the so-called minimum backoff B_{min} and the backoff period B_p , as given in Eq. 1 below.

$$d_B = (r \bmod (z \cdot B_p)) + B_{min} \quad (1)$$

where r is a 16 bit random value, $z = 31$ is the initial backoff factor on first transmission attempt and $z = 7$ is the congestion backoff factor utilized if the channel is sensed busy during any transmission attempt. In the latter case, d_B is drawn repeatedly until the medium is sensed idle again the overall lead time of which is recognized as MAD (see Section 2.2). On average, the smaller congestion backoff factor gives transmission reattempts higher priority over initial sending trials for fairness reasons. After d_B slot times of deferment, where $t_{slot} = 2 \cdot t_{symbol} = 32 \mu\text{s}$, the node is ready to send. By default $B_{min} = B_{per} = 10$ with B_{min} regarded as platform-specific covering all hardware-related in-system guard spaces and turnaround times and, thus, needs to remain constant for proper transceiver operation. Furthermore, its constant value has far less influence on MAD in contrast to B_{per} as initial experiments had shown. In terms of adjustable packet sizes, TinyOS implements IEEE 802.15.4-compliant protocol headers and footers accounting to 13 Byte by default which allows for additional payload lengths of up to 115 Byte, all in all referred to as P_S (see Section 2.2) in the following [24].

Due to possible activity of co-existing technologies, e.g., WLAN operating within the same frequency band, node transceivers are set to a channel providing for least collision potential [25]. The power amplifier is set to the highest level for sufficient transmission range and uninterrupted connectiv-

General Node Configuration		Experiment Run Configuration	
Parameter	Setting	Parameter	Setting
B_{min}	10 (320 μs)	B_P	[1,20] by 1
PAL	31 (0 dBm)	P_S [Byte]	[20,120] by 5
Channel	26 (2.48 GHz)	N_C	{1,2,4,8}
ACKs	0 (disabled)	Samples [packets]	1000
Duty Cycle	1 (always on)	Event rate [1/s]	10

Fig. 2: General and experimental configuration settings

ity of involved motes that are randomly arranged in a star-shaped topology with a radius of less than 1 m allowing for line-of-sight communication. For highly reliable and accurate delay measurements, an explicit TinyOS hardware timer abstraction named *Alarm* with μs precision and 32 bit of width is applied (as per timing precision evaluation of TinyOS timer abstraction settings in [26]). Besides, link-level ACKs are deactivated avoiding retransmissions of non-acknowledged frames for the sake of unambiguous measurement interpretation. All relevant configuration settings are summarized in Figure 2 (left).

The experimental testbed setup includes several MICAz motes, a gateway/programming board along with a Linux-based machine serving as *Evaluation System Node (ESN)*. One mote being attached to the gateway, henceforth *Run Controller Node (RCN)*, is in charge of test run coordination and relaying of results to the ESN via its serial connection interface. All other motes including the *Node of Interest (NOI)* are endowed with experiment run-specific execution settings and act as parts of a sample homogeneous WSN providing the RCN with feedback on gathered results. To this end, the RCN polls the NOI every now and then between experimental runs, collects measurement data and passes it to the ESN (see Figure 3).

During experiment run series, the RCN triggers the sending process of active motes by consecutively broadcasting control packets towards the network. This emulates an event shower situation, i.e., a kind of worst-case scenario for regional WSN operation, which implies concurrent action of topographically close entities. In that, we optimize our setup to isolate the actual cause for the phenomenon of packet loss being pure medium access collisions of involved nodes. Therefore, the broadcasts are guarded by 100 ms of inter-trigger lag to avoid node event overlaps. Hence, observations are unbiased which we support by a high number of samples helping to obtain fine-grained results for univocal analysis. In addition, the RCN acts as the receiving destination node in order to infer the PLR. For this purpose, the RCN keeps track of the number of received packets originated by the NOI. The measurement of the PSD, on its part, is conducted on the NOI during the sending process triggered by RCN control packets. Its value is included in the subsequent packet towards the RCN. The captured PSD covers the time duration from the initiation of the packet delivery process via the default TinyOS sending interface up to the

point when the event of successful modulation of the last packet bit is signaled by lower-layer TinyOS components.

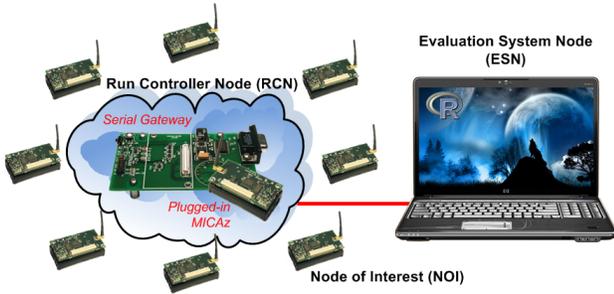


Fig. 3: Experimental testbed setup and network topology

Throughout all experimental runs, the three selected network parameters are systematically permuted over the specified range of values (confer Figure 2). Therefore, the backoff period B_p and packet size P_S are programmatically adjusted whereas the number of contending nodes N_C is controlled by turning them on/off manually. In order to obtain unambiguous information particularly on the number of lost data packets with high granularity, we set the number of triggered sending events to 1000 for each parameter constellation per experimental run.

B. Influence of B_P , P_S and N_C on Average Delay

As already indicated in Section II, the settings of the network parameters is assumed to have a significant impact on the performance properties under investigation. In order to proceed systematically, all influencing factors are regarded separately. To this end, Figures 4 and 5 include a subset of all experiment results for representative parameter constellations.

Figure 4 (a) reveals the developing of mean delays against an increasing backoff period also in view of four contender configurations while the packet length is minimized to 20 Byte. As can be clearly seen, the PSD increases gradually with all settings of the backoff period. Although it also shows a virtual dependency on the number of neighbors, the confidence intervals for 0.05 significance level overlap especially for higher backoff period values, signifying its statistical indistinguishability when it comes to the standard error of the computed mean from the real population mean. This is due to the increasing standard deviation of the samples lying between $776 \mu\text{s}$ and $5729 \mu\text{s}$ for no neighbors and between $1324 \mu\text{s}$ and $6044 \mu\text{s}$ for 7 neighbors, respectively, as far as backoff periods between 1 and 20 slots are concerned. This also emphasizes the high probabilistic impact, albeit ascertainable as almost linear, of the backoff period parameter on the overall delay. A more convincing statistical relevance of the number of contenders becomes evident not before the packet size is increased as exemplified for $P_S = 70$ Byte in Figure 4 (b), where, additionally, a slightly wider spreading of the confidence intervals and also a definite elevation of the PSD can be observed. The latter trend, which obviously suggest a sensitivity of the PSD to the packet length, is captured in Figure 4 (c). In terms of the default backoff period setting of 10 slots and incrementation of the packet length by 5 Byte

over the available range of values, the average PSD increases apparently in a linear manner as can be concluded visually from the diagram. Again, a severe statistical relevance of the number of contenders for the mean PSD, at least for the first two proximate instances of the traversed value range, cannot be assumed before a packet size of 50 Byte is reached.

For the sake of completeness, it shall be noted that throughout all experimental runs, we observed the devolution of the PPD (see Section 2.2) as well. It turned out that the PPD is exclusively dependent on the packet size P_S as expected. However, in order to shed light on its portion of the overall time readings in isolation, we conducted disjoint measurement runs freezing the random number to $r = 100$ for $B_P = 10$ within the backoff process, i.e., observing a constant MAD of $3520 \mu\text{s}$ for an initial backoff value of $z = 31$ as applied on first transmission attempt in case of only one sender. In this way, we numerically divided the PSD into its individual components, i.e., PPD, MAD, PTD, the relationship of which becomes evident in Figures 4 (a)-(c). Whereas the PTD can be assumed to be consistently dependent on the transceiver transmission speed, the measurements of the PPD yield a median standard deviation of about $11 \mu\text{s}$ proving its constancy in view of any parameter constellation. In summary, we can act on the assumption of a linearly proportional interconnection between the packet size P_S and not only the PTD but also the PPD the latter of which can be attributed to the preparation and in-system transfer of packet data between the microcontroller main memory and the radio transceiver transmission buffer [26].

C. Influence of B_P , P_S and N_C on Packet Loss

In contrast to the results on the PSD, the impact of the tested network parameters exhibits a partly different behavior with respect to the PLR. Intuitively, a wider range of the backoff delay interval implies a lesser chance of packet collisions in case more than one sender is actively probing for medium access. In effect, our field tests show a proportionally increasing PLR for an increased number of channel contenders N_C as depicted by Figure 5 which is persistently true for all parameter constellations. While a single sending node witnesses a PLR of approx. 0.1 % on the average due to system internal inaccuracies, 2, 4 and 8 contending senders can be subject to fluctuating PLRs of up to 92.8 % clearly depending on the backoff period and, at the first glance, also on the packet size when comparing Figures 5 (a) and (b). However, the impact on PLR shows divergent coherence in general when contrasting backoff period B_P against packet size P_S for decoupled parameter iterations. While the captured PLR obviously increases with a gradual decay of B_P in Figure 5 (a) and (b), there is almost no indication for a simply proportional relation between the PLR and P_S as shown in Figure 5 (c). The only noticeable observation remains the steady decline of the PLR from the highest packet size down to 45 Byte which thereupon reverts to a sudden remarkable increase followed by a nearly constant relaxation. This phenomenon appears to be connected to the general presence of channel contenders

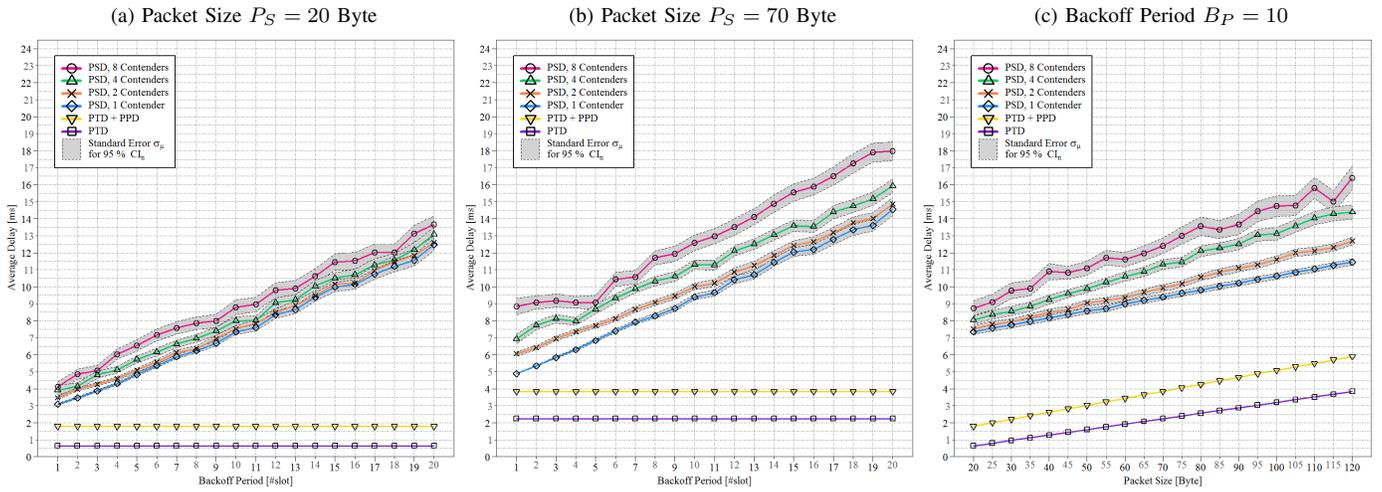


Fig. 4: Influence of backoff period, packet size, and number of contenders on packet transmission, processing, and sending delay

and might be accredited to an unbalanced number generation process with an unfavorable sequence of choices out of the value space. Nonetheless, from a statistical point of view, P_S appears to play a marginal role with regard to the PLR when considered in isolation. For this reason, we could limit our considerations to the adjustment of the backoff period which proved to be a valuable driver not only for the PSD but also the PLR. But, increasing PLR slope fluctuations as observed for all backoff period iteration series in combination with different packet sizes hypothesizes a potentially explicit correlation of those two network parameters that requires further contemplation. Other than that, the relatively small sample size for obtaining the PLR might also add to the encountered discrepancy, not to mention its implications on the precision of PLR predictions. In any case, there is clear evidence for a negative correlation of the PSD and the PLR which has to be taken into account when searching for the most appropriate parameter constellation including B_P . Contrary, the increase in number of contending nodes N_C results not only in an increased PLR but also in a higher mean PSD. In general, a higher PLR also adds to the E2ED in that it usually implies increased need for retransmissions and, thus, higher delays encountered at loss-intolerant applications which rely on the end-to-end protocol argument.

Summing up, the selected variety of presented experiment results reveals a couple of valuable insights into the characteristics of a concrete WSN node platform with regard to the I/EPSM approach. Based on these, prospective network entities shall be enabled to derive performance prediction models for the considered network properties next.

IV. PREDICTING PERFORMANCE PROPERTIES IN WSNS - A LIGHTWEIGHT YET POWERFUL METHOD

As part of the analysis principle of the I/EPSM approach, the determination of an appropriate performance model type along with its concrete instantiation based on available measurement results constitute the fundamental enabling procedure for meaningful estimation of performance property

values. A subsequent appraisal of enabled predictions against application requirements, in turn, will allow for an appropriate adaptation of selected network parameters for meeting imposed performance-related demands in a terminal step of the I/EPSM task cycle, the treatment of which, however, goes beyond the contents of this work. Also, any other modeling methodologies for value prediction based on, e.g., Network Calculus or Artificial Neural Nets might come into question as the foundation for the analysis principle further sophisticating the I/EPSM approach in terms of its flexibility. Yet, we focus on a lightweight yet powerful method as the most promising and demonstrably viable approach, even from the intrinsic point of view, for now as detailed in the following.

A. Regression Modeling and Analysis

One of the most common statistical methods for predicting random variables used by analysts is based on regression modeling [27]. A variety of regression techniques such as (curve) linear, non-parametric, mixed effects, a.o., exist to fit given observations of presumably related data into a corresponding model [28]. Usually, in order to identify and verify the right modeling technique as part of the modeling task within the I/EPSM task cycle, statistical tests are to be implemented on the corresponding network entities in charge. However, in view of our experimental outcome from Section III, simple and multiple linear regression emerge as most suitable for finding the performance model instance Ψ_i of choice that relates the network properties from tuple $\langle Y_t \rangle = \langle PSD, PLR \rangle$, each considered as predicted response y , to the nonstochastic network parameters x from set $\Phi = \{B_P, P_S, N_C\}$, that act as predicting explanatory variables according to Eq.(2) with $m \in \{1, 2, 3\}$.

$$y_{r_t} = r_0 + \left(\sum_{i=1}^m r_i \cdot x_i \right) + \epsilon, x_i \in \Phi \setminus \bigcup_{k=1}^i x_{k-1} \quad (2)$$

where $x_0 = \emptyset$, $t = \{0, 1\}$, r_i are regression coefficients, and ϵ denotes the residual error term.

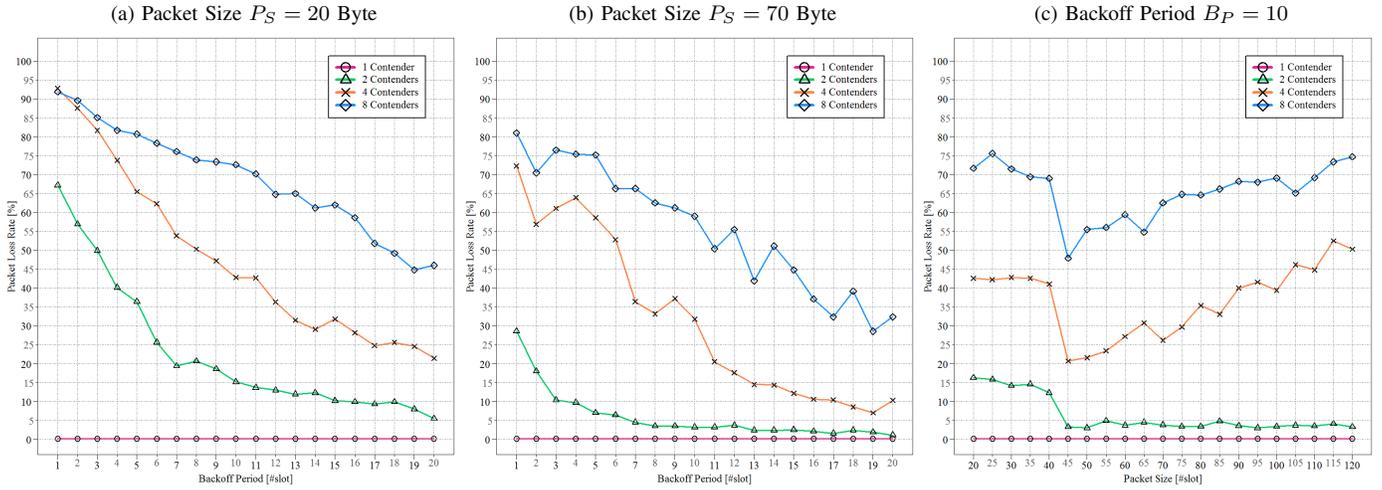


Fig. 5: Influence of backoff period, packet size, and number of contenders on packet loss rate

In the course of singling out the best fitting model variant Ψ_i for any of the 7 distinct parameter constellations per element of Υ , we consider our entire set of measurement results. Since we accomplished 492 experimental observation runs in total covering more than 29 % of all possible combinations within the defined value range bounds for all 3 network parameters while capturing up to 1000 samples per run, we can rely on 488 up to 490 degrees of freedom for the statistical estimation of regression coefficients provided that the model errors are independent and subject to a Gaussian distribution with zero mean and constant standard deviation.

In the first place, we derive a simple linear regression model to relate the properties in Υ to any individual network parameter from Φ in a linear fashion. Subsequently, both network properties are considered in view of all possible combinations of those parameters by virtue of a multiple linear regression model each. In order to find the mean predicted response with as little variability as possible, we apply the least-squares criterion procedure minimizing the sum of squared errors in view of the observed mean response y_j as per Eq. 3 for all n observations. The result summary is tabulated in Figure 6 (left).

Expectedly, the results show that any of the network parameters has a distinct influence on any of both properties to a certain extent as can be told by the corresponding *Coefficient of Determination* (Ω). In fact, Ω discloses how much of the variation of the response variable is explained by the regression as the measure of choice when comparing the predictability relevance of fitted regression values of different models [28]. On this note, Ψ_1 based on just the backoff period appears to have highest single explanatory rate of about 62.53 % on the PSD in contrast to the number of contenders N_C that seems to play just an inferior role with only 9 % as already anticipated in Section III. Nevertheless, its combination with the other two parameters within model variant Ψ_7 is assumed to most precisely explain the PSD on the average by 97.56 %, i.e., it can predict its mean value more reliably than all the other models do. On the other hand,

Ψ_3 turns out to have by far the highest explanatory value of 65.82 % regarding the PLR while the pure influence of the packet size P_S seems minuscule in accordance with our experimental evaluation. Again, the combination of all three network parameters in Ψ_7 results in the most optimistic model instance, albeit, not significantly more than Ψ_5 which is based on just two of these.

$$\min \left[\sum_{j=1}^n (y_j - y_{\tau_t, j})^2 \mid \frac{1}{n} \sum_{l=1}^n \epsilon_l = 0 \right] \quad (3)$$

B. Performance Model Validation in Multi-Hop Scenarios

From an analytical perspective, a best practice for choosing the right model is to compare the statistical relevance of regression for all constellations of available predictor variables. However, whereas the implementation of deducing regression coefficients along with Ω is rather straightforward, their further validation implies more involved operations including, a.o., distribution generation, normality proofing, and result transformation. Whereas some of these may remain delegated to an external network entity subject to EPSM, we focus on an approved subset of viable validation candidates for further integration into IPSM-driven node implementations.

In this context, examining the *Confidence Intervals* (CIs) for the regression coefficients of a model offers valuable clues to the variability of these estimates. Concurrently, testing CIs also reveals if the regression explains a significant part of the variation of the response variable. In case the CI does not include zero, the coefficient of the variable is said to be non-zero and thus the regression is statistically significant and vice versa. Whereas this holds true for even a 0.05 significance level for any single predictor variable tested against PSD as in isolation so in combination, this assumption cannot be generally anticipated for PLR estimation, particularly in case of multiple response drivers as present within model option Ψ_4 . This is due to potential multicollinearity effects of the predictor variables that counterintuitively might reduce the

Model	PSD PLR	Coefficient of Determination		Non-Zero Confidence Intervals		Zero Parameter Correlation
		Ω_{PSD_i} [%]	Ω_{PLR_i} [%]	PSD	PLR	
Ψ_i	~					
1	B_P	62.53	16.07	✓	✓	-
2	P_S	26.03	0.41	✓	✗	-
3	N_C	9.00	65.82	✓	✓	-
4	$B_P + P_S$	88.56	16.48	✓✓	✓✗	✓
5	$B_P + N_C$	71.53	81.88	✓✓	✓✓	✓
6	$P_S + N_C$	35.03	66.22	✓✓	✓✓	✓
7	$B_P + P_S + N_C$	97.56	82.29	✓✓✓	✓✓✓	✓

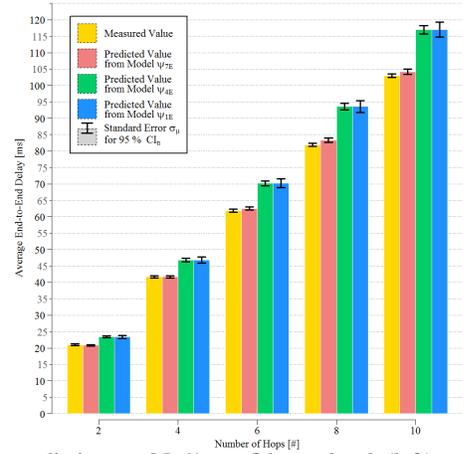


Fig. 6: Statistical significance indicators of linear regression models for PSD and PLR prediction at 95 % confidence level (left) and comparison of model prediction quality for E2ED in multi-hop scenarios under defaults $B_P = 10$, $P_S = 70$ Byte, and $N_C = 1$ (right)

statistical accuracy of the applied regression method. However, the sighted incongruity regarding the packet size parameter merely reflects its irrelevance in view of PLR prediction as already foreshadowed in the previous section. Apart from that, all network parameters pass the corresponding zero correlation test and clearly exhibit an additive cohesion throughout all model alternatives, both of which indicate their uncorrelated pertinence for response prediction (confer Figure 6 (left)).

In the course of a proof of concept for the analysis principle within the IPSM inspection phase, we also implemented the linear regression method on a real WSN mote. The results confirm that the alleged resource limitations do not hamper the feasibility and precision of the very modeling and prediction technique at all. However, the implementation of a dynamic storage management necessary to handle the vast amount of sample data effectively within the pretty slow flash storage, offering a mean access time of about 4 ms per observation, challenged the hardware in terms of 25% leftover main memory during execution. A moving average function implemented to consider only the last captured value into a continuously updated mean PSD for every network parameter setting constellation from Φ , turned out to be significantly close to the mean over the entire measurement set. In this manner, just a subset of values of $(\|\Phi\| + 2) \cdot 4\text{ Byte}$ for each compound observation with μ s precision for PSD was stored to conduct the sequence of calculations needed for regression model instantiation[28].

Since further considerations might imply more complex and partly divergent decisions depending on the used modeling technique that go beyond simple numerical operations as state before, we dedicate our regard to a pragmatic comparison of enhanced prediction results to measured E2ED values for some basic multi-hop WSN scenarios as follows.

Based on the original experiment setup, we organized hop-variant network topologies of tandem-like shape and measured the E2ED (where PLR would work analogously) between the source and the destination node for default parameter settings as per Figure 6 (right). Apart from the PSD as estimated by a subset of most promising model instances selected based on

Ω , we amplify our models by including the PPD, which is assumed to additionally incur at every receiving node r , and by postulating an additive coherence between the E2ED and the number of hops h according to

$$y_{r_1,E} = h \cdot \left(y_{r_1} + \frac{1}{2} PPD_r \right) \quad (4)$$

Indeed, yield results show an almost perfect forecast of the E2ED for up to 10 hops using enhanced model Ψ_{7E} as indicated by overlapping CIs for 95 % confidence level. Other model candidates, in turn, seem to mismatch the E2ED to a large extent. Interestingly, the prediction based on Ψ_{1E} is equal to that based on Ψ_{4E} , albeit, with a lower certainty, even though P_S is unconsidered in Ψ_{1E} and $\Omega_{PSD_1} < \Omega_{PSD_4}$. This example points out the importance of diversity in consulting statistical measures when comparing prediction quality. Nevertheless, a general trend towards overestimation of the E2ED by any model can be observed that seems to sum up with the increase in number of hops. This either suggests a missing influence factor or just a misconception of the considered ones. In fact, in our case, the PPD as part of the sending process verifiably differs from the PPD during reception by about the half as prior node-local measurements revealed. Again, this result illustrates that a performance model can only be as good as the knowledge about the integral parts its prediction is based upon. That is why, prospective self-managed network entities are meant to collect or conclude as many details about their constituent parts as possible adhering to the I/EPSPM control principle.

Summing up, whereas model type selection and definite model validation remain out of scope for resource-constrained devices for now, we verified the investigated modeling technique to be what a WSN node is able to apply for meaningful performance model derivation in virtue of its given capabilities. This is in line with our original aim to keep computational costs and complexity as rational as possible rendering the methodology what is considered lightweight and eligible for the I/EPSPM concept.

V. CONCLUSION AND FUTURE WORK

This work dealt with an introductory investigation of a measurement-based approach to self-management of performance-related network properties based upon a common methodology for stochastic value prediction. We have conducted extensive measurements to determine the influence of three selected network parameters on two fundamental network properties. A concise overview of applied technology, experimental design, and theoretical background introduced the basis for our drawn conclusions. Our main results confirmed previous assumptions of a linear relationship between packet sending delay and backoff period, packet size, as well as number of contending nodes for diverse networking scenarios. Further findings on packet loss rate and its relation to the parameters in question have been obtained, e.g., proneness to fluctuations for certain influence factor variations. Furthermore, we derived several regression models based on empirical data enabling property forecast for arbitrary parametrical settings even on a resource-scarce WSN mote. A subsequent model validation followed by a practical verification of yield speculations on performance behavior in basic multi-hop networks finally revealed the high precision of an augmented performance model in view of end-to-end delay prediction. All in all, we have demonstrated viable methods for the aspired measurement and modeling tasks based on principles as part of our comprehensive I/EPsm approach that bears good prospects due to its flexibility in further integration of analysis methods along with load-balanced collaboration techniques in future concretions. In this context, we aim at considering lightweight procedures with as little demands on computational resources as possible by using network inherent information that can be drawn from regular network node operation and communication behavior.

As part of future work, we intend to explore further WSN peculiarities as influencing factors, e.g., duty cycling and data-aggregation, and also test the quality of prediction for network properties other than the ones considered herein. Also, various other networking scenarios shall be subject to complementary future investigations. In order to cover more involved network topologies and parameter interactions, simulations constitute the basis for obtaining comparative results for larger-scale networks. Finally, in view of our long-term research endeavors, the implementation of sophisticated routines for model validation purposes along with the integration of other property prediction techniques on a unified infrastructure for network autonomy are also up to future work.

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