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Data Filtering for Wireless Sensor Networks Using Forecasting and Value of Information

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***Abstract*—Energy constitutes a scarce resource in wireless sensor networks, making energy-efficient operation mandatory. Data transmission has been identified as one of the most energy consuming operations. Consequently, different approaches to reduce data transmissions have been proposed, like data filtering. Recently, the value of information of sensor data has been identified for data filtering, explicitly incorporating application-specific and context-dependent information needs. The filtering is done according to the benefit a data transmission would induce at the recipient. We propose an on-mote filtering approach, which relies on local multi-step assessment of sensor data with forecasting and assessing value of information. We apply our approach to logistics transport processes and evaluate it concerning number of data transmissions and energy efficiency. Our simulation results showed that with our approach the number of data transmissions and the energy consumption can be reduced by over 25% to over 60%, while simultaneously accounting for user-specific information desires.**

I. Introduction

Energy-efficient operation is mandatory in a wireless sensor network (*WSN*), because wireless sensor nodes (*motes*) typically employ batteries as their primary power source. Thus, the energy budget of a mote is restricted and means to enhance its efficient usage are required to enable a prolonged network lifetime.

As a consequence, substantial research work has been conducted to realize energy-efficient data transmission (cf., for example, overviews in [1], [2]). However, data transmission generally still consumes more energy than data processing [3]. Thus, filtering data locally on motes has been identified as a promising solution to enhance the energy efficiency in WSNs by efficiently reducing the number of data transmissions [4], [5]. Such local data filtering furthermore allows for realizing potential monetary savings and consequently enhancing cost efficiency in a WSN deployment. This is for example achieved due to reducing the number of data transmissions to users' backend systems, which might require the usage of communication technology liable to fees, as for example in the context of WSN deployments in logistics where it might be necessary to transmit sensor data to backend systems using satellite connections [6].

Recently, several data filtering approaches have been presented in the context of WSN research. As one very promising approach, using the value of information of sensor data as a basic filtering criterion has been identified (cf. [7]). The basic idea in this context is to explicitly incorporate a user perspective for determining the value of information of sensor data to account for users' information demands within the filtering decision and thus consider the corresponding benefit the transmitted data would induce on the user side. With such a user-centric filtering, the number of data transmissions can be reduced while still providing a sufficient data fidelity from a user's perspective. Therefore, we describe a local data filtering approach, which employs two different concepts in subsequent filtering steps, namely data forecasting and value of information. Consequently, we explain how such data forecasting and value of information determination can be locally realized and how corresponding data filtering decisions can be taken on motes within WSN deployments in the application domain of logistics (*logistics WSNs*). Thus, the major contributions of this paper are:

- A concept for local data filtering based on forecasting and value of information.
- Local forecasting methods for estimating the future evolution of measured sensor data.
- A method for determining the value of information of sensor measurements.
- The prototypical realization of the developed methods and their evaluation with respect to the number of data transmission and energy efficiency.

The remainder of this paper is structured as follows: Related work is provided in Section II. In Section III, we outline the considered application scenario and our multi-step approach for local data filtering. The forecasting methods employed within the first filtering step are described in Section IV. Section V focuses on the value of information determination used within the second step of our approach. The evaluation of our approach is presented in Section VI. We conclude by summarizing our findings and giving an outlook on future work in Section VII.

II. Related Work

Local on-mote data filtering approaches on the basis of context data evaluation have basically already been devised in the context of different WSN routing approaches, like SCAR [8], EMA [9], or EM-GMR [10]. From a more application-specific point of view, Jedermann et al. as one example have as well pointed out that shifting decisions to individual motes is a promising means to reduce communication and correspondingly leads to extended battery lifetimes of motes [3]. In this respect, several approaches for local on-mote filtering in a broader logistics context have already been presented.

In the context of their approach for efficient and secure sensor reprogramming within logistics WSNs, Evers and Havinga outline an option for autonomously verifying correct handling conditions during a transport process [11]. They focus on the detection of temperature violations and corresponding transmissions of alarm messages. However, they base the decision to transmit a corresponding alarm message only on the isolated assessment of a single context parameter, not realizing an in-depth assessment of the data in question.

Marin-Perianu et al. as well explicitly advocate the realization of a local logic on motes for saving network communication overhead and costs by deliberately reducing the transmission of data to sensor measurements, which violate specified conditions [12]. They propose to employ a rule engine on motes, which allows for a mapping of simple business logic on rules which then can be evaluated locally by the engine. In case the rule engine detects a violation of a given condition, it initiates a corresponding reaction, like the transmission of a corresponding message to a backend. Yet, the authors focus their research work on how an efficient distribution and update of rules can be achieved, and propose a corresponding tree-based dissemination protocol.

A distinct focus on employing rules within a logistics WSN has been employed by Son et al. [13]. In their approach, motes check whether selected sensor measurements violate given intervals as specified by corresponding rules. However, the authors have not explicitly foreseen linking different rules, and consequently do not take different possible parameter interdependencies for into account.

Concerning the concept of value of information in sensor networks and its specific application in the domain of intruder tracking sensor networks, Turgut and Bölöni have provided seminal work in [7]. There, the authors understand sensing quality based on "the pragmatic value of the information provided by the network" [7] and argue that such a quality metric has to explicitly incorporate the end user perspective. This means that the value of information assigned to sensor data is pragmatically determined by explicitly taking into account users' interests and the decisions taken by users on the basis of the data received from the network. Within their system, network nodes only forward those messages that exhibit the highest value of information. The authors could show that the value of information experienced by users in such a system can be significantly increased with their approach.

The filtering decisions realized within the described approaches usually rely on a relatively strict and static basis, whereas our approach allows a more-fine grained decision explicitly incorporating various application-related aspects. Thus, reducing data transmissions and simultaneously providing users with data more meaningful can be realized with our approach by explicitly allowing to integrate a more complex logic for the local filtering decision and thus accounting for context-dependent individual information needs. We follow the approach outlined in [7] of assessing sensor data based on value of information and transfer and operationalize this approach to the domain of logistics WSNs by developing a method to determine the value of information of sensor data in this application area.

III. Local Multi-Step Data Filtering

A. Application Scenario of Logistics WSNs

The basic approach of our multi-step local filtering concept and the methods of forecasting and value of information determination for the filtering decisions constitutes a general approach, usable independent of a specific application domain. However, the operationalization of this approach, and in particular the value of information determination, is strongly application-specific (cf. [7]). As the logistics domain constitutes a particularly promising field for the application of WSN technology (cf. [3]), we employ the area of logistics transport processes as basis for the application and consequent operationalization of our approach. Within such a transport process, motes can be deployed for example in a container or a truck's load area to monitor diverse environmental parameters relevant to the transported goods' conditions, locally assess the sensor measurements and wirelessly transmit alarm messages via corresponding gateways in case a critical situation has been detected in real time. Based on such real-time notifications, the early initialization of adequate countermeasures becomes possible. Example applications in this context are temperature monitoring in the case of transporting temperature-sensitive goods, like food or medicine, tilt and shake monitoring for tilt- and shock-sensitive goods, like displays, or monitoring of gas concentrations during food and animal transports.

B. Multi-Step Filtering Concept

The basic task for our multi-step filtering concept consists of the context-dependent interpretation of sensor measurements to assess these measurements and thus taking the decision to initiate a transmission of the sensor data or not and accordingly filter out the data. Our approach comprises two components to realize this task. A "measurement execution and analysis" component and a "selective transmission" component (cf. Fig. 1). The first filtering step within the "measurement execution and analysis" component performs a data categorization into three different categories based on data forecasting. After this categorization, depending on the assigned category, gathered sensor data is either filtered out directly or selected for a more detailed assessment within the "selective transmission" component. For this second fine-grained assessment of the sensor data and the subsequent final filtering decision, the value of information of the data is determined and compared against the transmission costs, a transmission of the data in question would incur. In case this comparison yields a positive result, i.e., the value of information outweighs the transmission costs, the corresponding sensor data is transmitted. Otherwise,

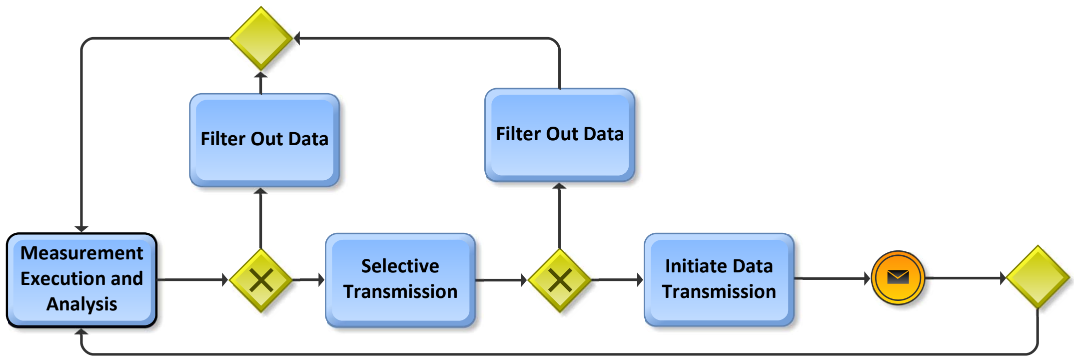


Fig. 1: Overview of our multi-step filtering approach

i.e., in case the transmission costs outweigh the value of information, the data is not sent, but filtered out.

IV. Forecasting for Sensor Data Classification

Local forecasting allows to make an assumption concerning the future development of a measured environmental parameter and constitutes the central criterion for classification of the corresponding sensor data within our "measurement execution and analysis" component. Consequently, it becomes possible to not only assess the current state, but to identify potential (critical) future states as well. Therefore, we do not categorize sensor data only as critical or uncritical, but as well as potentially critical, i.e., potentially becoming critical in the future. We understand a critical state as a state where a given threshold for a measured parameter relevant to the transported good's health is violated. Accordingly, we make use of three different categories with a "green" state, a "yellow" state, and a "red" state (cf. Fig. 2).

In order to locally derive the estimation of the potential development of a measured parameter constituted by the read in sensor data to be assessed, we compare the gathered sensor data against historical data. In this context, different forecasting methods can be employed. A very popular method is linear regression (*LR*), which employs a "regression line" to establish a functional relationship between the measured values. On the basis of this regression line, a mathematical function is deduced with which the forecasting of future values is realized. However, LR is rather prone to outliers and therefore the forecasting quality suffers from such outlier values within the historical data used to determine the regression line. To overcome such problems and to incorporate measurement values dating further back within the forecasting, the method of single exponential smoothing (*SES*) can be employed. With this method, historical values can be incorporated by making use of a recursive approach without having to store all values (cf. Eq. (1)). Furthermore, a smoothing factor is employed, which makes SES more robust against errors of measurement and shocks in the underlying data basis. SES has been developed further to the method of double exponential smoothing (*DES*) to explicitly allow for accounting of trends in the forecasting. Therefore, DES uses two distinct components. One component accounts for the level and one for the trend of the underlying data basis. The forecast level corresponds to the intercept within LR and the trend corresponds to the slope. As initialization step in DES, the first considered measurement value is used as level component and the difference between first and second considered measurement value is used as trend component. The further computation of the level and trend component and the actual forecasting computation within DES is described in Equations (2) to (4). In the context of our approach, we implemented all three forecasting methods and compared them to each other (cf. Sec. VI).

$$y_{p+1} = \alpha * y_p + (1-\alpha) * y_{p-1} \tag{1}$$

$$y_{p+h} = l_p + h * b_{p-1} \tag{2}$$

$$l_p = \alpha * y_p + (1-\alpha) * (l_{p-1} + b_{p-1}) \tag{3}$$

$$b_p = \beta * (l_p - l_{p-1}) + (1-\beta) * b_{p-1} \tag{4}$$

TABLE I: Table of notations I

Notation	Description
y_x	Value for time period x
p	Time period
h	Number of forecasting time periods
α	Smoothing parameter for level component
l_x	Level component in time period x
b_x	Trend component in time period x
β	Smoothing parameter for trend component

Based on the actual sensor measurement and the corresponding forecasting results, the classification of the sensor data in the three mentioned categories is carried out on the mote. As basis for the actual categorization in the context of our considered application scenario of transport monitoring, corresponding product-specific thresholds which influence the health of the monitored goods can for example be used. Consequently, sensor data would be assigned to the category "green" in case the actual sensor data and the locally computed forecasting value do not exhibit any threats to the transport good. In this case, the measurement value is not transmitted,

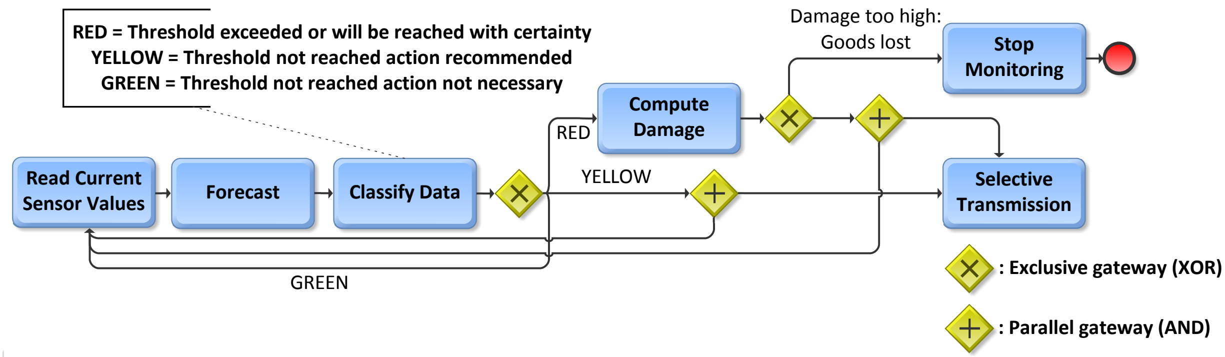


Fig. 2: Measurement execution and analysis component

but only stored locally to be used as historical input for the next forecast computations.

A sensor measurement is categorized as "yellow" in case the current sensor sample does actually not pose a threat to the transport good's health, but the forecasting indicates that a critical threshold violation is likely. This exhibits a (potential) threat for the transport good's health accompanied by a corresponding (potential) loss of value of the transport good due to (potential) damage. Accordingly, the sensor data is not filtered out directly, but forwarded to the next component, "selective transmission", to further decide on its transmission relevance.

Finally, a sensor measurement is assigned to the category "red" in case the measured data already indicates a threshold violation or the forecasting value indicates that such a threshold violation cannot be prevented even by initializing countermeasures externally, like significantly reducing the temperature via a reefer module in the example of monitored reefer transport. Such a situation would indicate inevitable damage to the transport good and subsequent loss of value due to the damage. We further derive the extent of the consequences of such a threshold violation by calculating the integral over the amount and time of the threshold violation. This provides a good indicator how severe the damage to the transported good is and for example whether the monitoring should be continued or the transported goods are completely lost and thus the monitoring can be stopped. However, in case a continued monitoring is beneficial, the thresholds will be adjusted so that in the future an earlier categorization of the measured sensor values into the "yellow" category takes place, which allows to avoid further damage by detecting potentially critical parameter developments earlier. Finally, the measured sensor data is forwarded to the "selective transmission" component to determine its value of information and finally decide on its transmission or filtering.

V. Local Value of Information Assessment

Within our approach, the "selective transmission" component is responsible to finally decide whether sensor data is transmitted or filtered out. This filtering decision is taken on the basis of the value of information of the sensor data in question.

At the point where a packet has already been queued for transmission by the "measurement execution and analysis" component and been handed over to the "selective transmission" component, it must at least belong to the categories "yellow" or "red" (cf. Section IV). Thus, a (potentially) critical situation has already been detected and consequently a basic value of information is already present, as otherwise the sensor data would belong to the "green" category and would not have been queued for a potential transmission. In consequence, we assume that users are primarily focused on a desire for process control and that their desire for pure process transparency is much lower. This means that users primarily want to be able to control their processes. Thus, as every sensor measurement belonging to either the category "yellow" or "red" constitutes data relevant for process control, it possesses a basic value of information, because the sensor measurement indicates that it is necessary to initiate an action to address the consequences related to a (possible) violation of a threshold constituted by the actual sensor measurement or its deduced forecasting value. A sensor measurement belonging to the "green" category does not require an action on the user side. Therefore, it is assigned no basic value of information. However, as already pointed out, within our approach the "yellow" and "red" data queued for transmission is further analyzed and its value of information determined. On the basis of this analysis, it is either transmitted afterwards or excluded from transmission and filtered out. In the following, we will focus on this data analysis based on the value of information of sensor data and how a utility value as operationalization of the value of information of sensor data can be assigned to sensor data locally on a mote.

The focus of WSN deployments in logistics transport processes is usually on monitoring environmental parameters influencing the health of the transported goods and detecting violations of corresponding thresholds which might lead to the damage of the transported goods (cf., e.g., [14]). Thus, logistics WSNs explicitly focus on the supply quality within a logistics transport process. Additionally, the delivery of damaged goods, or rather the delivery of only those goods which are still intact from the initially targeted amount of goods having suffered from a critical threshold violation of an environmental parameter, affects the amount of correctly delivered goods. Therefore, the supply quantity can as well be positively affected by realizing a real-time monitoring of transport processes with WSN technology and the corresponding prevention of such damage by detecting critical environmental parameters in time and reacting to them.

As already indicated, we interpret the value of information of gathered sensor data, according to a pragmatic value of information concept as for example presented in [7], as the utility created at the data's intended recipient, in the application scenario considered here, a responsible decision maker in a logistics transport process. This utility has to be valuated to provide a basis for decision-making locally on a mote with regard to whether the sensor data in question should be transmitted or not. For this valuation, we relate the utility, in the sense of the concept of opportunity costs, to the costs avoided by initializing a countermeasure due to the sensor data transmission in response to the detected (potential) threshold violation and thus the corresponding avoidance of quality and quantity loss of transport goods as described above due to the countermeasure. In consequence, the opportunity costs to be considered can be interpreted as originating from the consequences of a quality and/or quantity loss of the transport goods in case the sensor measurement data would not be transmitted and thus the responsible decision maker would not be informed and consequently no corrective action would be taken. As a consequence, we propose to calculate the monetary value of these potential quality and/or quantity losses as opportunity costs and thus as utility and value of information of the sensor data to be assessed.

In this context, the effects of a violation of the mentioned quality and quantity targets can basically be used to deduce a monetary valuation of the goal violations themselves and thus the value for the opportunity costs for not transmitting the sensor data in question constituting the data's value of information. Such effects can be differentiated into deterministic and non-deterministic effects.

Deterministic effects comprise directly determinable effects. Thus, deterministic effects can be valuated and consequently monetarized based on directly arising costs. In the considered application scenario such effects are constituted by price reductions, contractual penalties, reworking and/or replacements costs, and contribution margin losses (cf. Tab. II and Eq. (5)) due to reduced margins on sales and lost sales, multiplied by the duration of shortage (cf. Eq. (6)) originating from the quality and/or quantity loss of the transport goods (cf. [15]).

$$ML = (RU - VC) * (DT * \frac{D}{WD} - PS) \tag{5}$$

$$DS = \frac{(DT * \frac{D}{WD}) - (PS + TS)}{\frac{D}{WD}} \tag{6}$$

Opposed to deterministic effects, non-deterministic effects comprise effects, which cannot be directly determined and monetarized, because they possess for example a huge set of influencing factors or factors which are subject to high uncertainties, as their development is based on decisions in the future. Such effects are for example taken into account in companies' balance sheets in the terms of changes in the enterprise value or loss of good will. Consequently, this is rather an immaterial value, which influences the future development of a company or its image. It can be expressed as loss of good will as depicted in Eq. (7) (cf. [15]).

TABLE II: Table of notations II

Notation	Description
ML	Contribution margin loss
RU	Revenue per unit
VC	Variable unit costs
DT	Downtime
D	Demand per period
WD	Workdays per period
PS	Planned safety stock
DS	Duration of shortage
TS	Transfer stock
ΔL	Loss of good will
M_0	Planned contribution margin
CL	Customer loss probability
NO	Average number of orders per customer
i	Imputed interest rate
g	Predicted growth rate
VoI	Value of information
ΔP	Price reductions due to discounts
ΔRC	Reworking and/or replacement costs
CP	Contractual penalties
$rEnC$	Relative energy cost coefficient
PT	Planned process time
t	Current time within the logistics transport process
EnB	Total energy budget
REn	Remaining energy budget
EnC	Energy costs of data transmission
$rComC$	Relative communication cost coefficient
$ComB$	Total communication budget
$RCom$	Remaining communication budget
rCC	Relative countermeasure cost coefficient
CB	Total countermeasure budget
RC	Remaining countermeasure budget
TC	Transmission costs
CC	Countermeasure costs
$ComC$	Communication costs
OC	Coefficient for fictitious loss due to mote outage

$$\Delta L = M_0 * CL * NO * \frac{1}{i - g} \tag{7}$$

Having accounted for deterministic and non-deterministic effects of violating quality and quantity targets within the logistics transport process due to undetected threshold violations, respectively not informing according users of such threshold violations, these can now be combined to determine the opportunity costs for not transmitting the sensor data to be valuated and consequently derive the data's value of information (cf. Eq. (8)).

$$VoI = min(ML * DS, \Delta P) + \Delta L + \Delta RC + CP \tag{8}$$

To finally determine whether the gathered sensor data should be transmitted or not, and thus take the data filtering decision, the deduced value of information has to be compared to the costs for the potential data transmission. In case these costs outweigh the value of information, the gathered data will not be transmitted and thus will finally be filtered out.

Concerning the determination of the data transmission costs, we consider three different cost categories with the energy costs, as the energy expenditure on a mote needed to transmit the data, the communication costs, as the monetary expenses needed for a long-range data transmission from the WSN to a backend system, and the countermeasure costs, as the costs accruing for realizing an adequate countermeasure to the transmitted critical data. In this context, we assume that for all three cost categories a fixed budget exists, e.g., the charge of the batteries employed as power sources for a mote and an upper bound for acceptable monetary expenses, each for data transmissions from a WSN to backend systems and for realizing countermeasures to critical states. These budgets have to be related to the actual remaining budgets at the point of time when the valuation on the mote takes place and additionally set in relation to the remaining time of the transport process, for example as one indicator for the required remaining lifetime of the WSN. Therefore, we deduce three different relative factors (cf. Eqs. (9) to (11)) with which the actual expenses for data transmission, with regard to the three mentioned cost parameters, have to be discounted at the point of time of the value of information determination. Furthermore, we employ a coefficient for a fictitious network breakdown due to a mote having run out of energy to account for the corresponding (fictitious) future costs of not being able to provide the real-time monitoring with the WSN anymore and the corresponding risk of not being able to detect critical situations anymore.

$$rEnC = \frac{PT - t}{PT} * \frac{EnB}{REn + EnC} \tag{9}$$

$$rComC = \frac{PT - t}{PT} * \frac{ComB}{RCom} \tag{10}$$

$$rCC = \frac{PT - t}{PT} * \frac{CB}{RC} \tag{11}$$

Using the three described relative coefficients, the transmission costs for the potential data transmission can be derived as sum of the accordingly discounted costs of the three different cost categories of energy costs, communication costs, and countermeasure costs as depicted in Eq. (12).

$$TC = rCC * CC + rComC * ComC + rEnC * OC \tag{12}$$

Finally, if the difference of the local on-mote computations of the value of information (Eq. (8)) and the transmission costs (Eq. (12)) based on the corresponding context-dependent and in parts user-defined product-specific parameters yields a value equal or greater than zero, the "selective transmission" component initiates the transmission of the valuated sensor data, otherwise the sensor data in question is filtered out and no transmission initialized.

VI. Evaluation

A specifically promising application field for logistics WSNs is real-time monitoring of transport processes of temperature-sensitive goods, because, e.g., in the context of food transports product losses due to temperature mismanagement and quality decay can reach up to 35% [16]. As a consequence, we based our evaluation experiments on a real-time monitoring scenario in the context of transport processes comprising temperature-sensitive goods.

A. Evaluation Setup

For our evaluation experiments, we used the COOJA/MSPSim simulation environment [17] with the TelosB mote [18] as underlying mote platform. The TelosB platform exhibits a wide dissemination within WSN research and has furthermore already been employed in logistics WSNs [19], [14]. COOJA/MSPSim offers the opportunity for network-level simulations in combination with means to analyze the energy consumption of algorithms on the basis of hardware emulation.

As our approach is focused on the filtering decision based on the logic described above, it abstracts from underlying MAC protocols and lower layer optimizations. Consequently, we employed the NullMAC protocol implementation within our simulation experiments, which means that the sender radio is only switched on for packet transmissions. To ensure reproducible results, the employed data sets have been statically supplied to the simulated application.

Concerning the calculation of the energy demand of the different approaches evaluated, we assumed an operation voltage of 3V and current consumptions for the radio of 18.61mA in listening and idle mode, 18.24mA during transmission, and 5.1μA in inactive mode [20]. With respect to the remaining TelosB platform, current consumptions of 1.8mA for the active state and 5.1μA in the sleep mode [18] have been assumed. The initial energy budget within our simulations has been set to 10,000J, roughly equivalent to the charge of two rechargeable AA cells. Finally, a duty cycle of 60 seconds has been employed, which leads to a new sensor sample and a corresponding transmission opportunity once every minute.

We employed two different real-world temperature traces (*RealTrace1*, *RealTrace2*) within our simulation experiments (cf. Fig. 3) to assess different behavior in the context of real-world settings:

- *RealTrace1* represents a temperature trace for a transport of temperature-sensitive goods over seven days obtained on the basis of linear interpolation of data provided by a major logistics service provider.
- *RealTrace2* represents a temperature trace for a transport of temperature-sensitive goods over five days obtained on the basis of linear interpolation of temperature data published in [6].

B. Evaluated Monitoring Approaches

For the evaluation of our filtering approach, we compare our approach on the basis of the number of data transmissions and

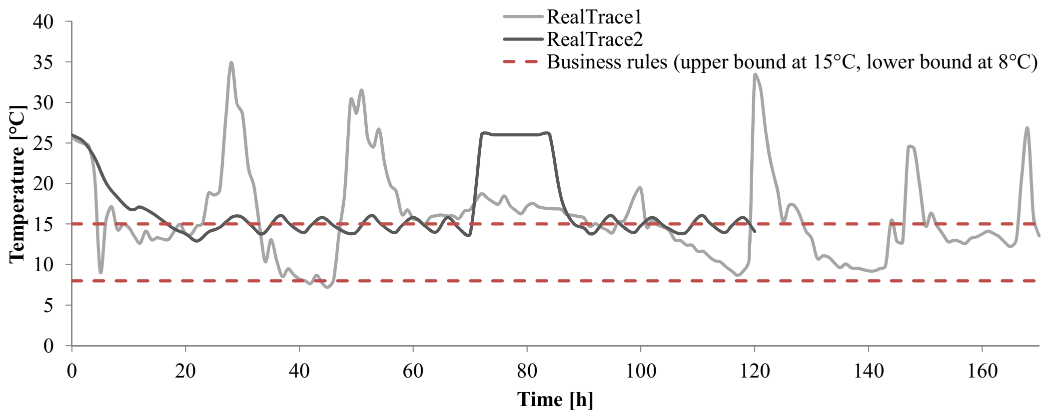


Fig. 3: Temperature traces *RealTrace1* and *RealTrace2*

remaining energy of a mote at the end of the simulated transport to two other monitoring approaches currently prevalent in logistics:

- Periodic monitoring (*Per*) constitutes a simple monitoring approach, in which environmental sensor data is gathered and transmitted regularly by a mote according to defined intervals.
- Business rule-based monitoring (*BR*) is based on regular sensor sampling as well, but restricts the transmission of gathered data to sensor samples, which violate static product-specific thresholds as pre-defined by so-called business rules, which provide upper and/or lower bounds as critical values for environment parameters relevant to transport goods' conditions (cf., e.g., [13] and Sec. IV).

As a consequence of our duty cycle setting of 60 seconds, the *Per* approach initiates a data transmission every minute within our simulations. With regard to the operationalization of the *BR* approach, we based the required thresholds on critical temperature values for the transport of tomatoes (cf. [6]), as a temperature-sensitive transport good. This leads to a lower threshold of 8°C and an upper threshold of 15°C (cf. Fig. 3). As product-specific critical values, these thresholds have as well been employed as categorization thresholds to detect critical situations within our approach (cf. Sec. IV). Furthermore, we employed the settings depicted in Tab. III for our multi-stage approach in the conducted simulations.

C. Evaluation Results

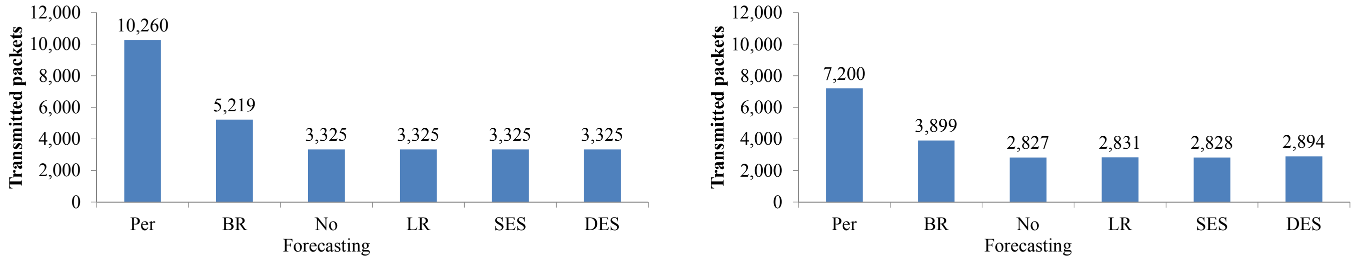
Figures 4 and 5 present the results of our simulations, displaying the cumulative number of data transmissions and the remaining energy budget after the end of the simulated transport. As intuitively expected, the results show that the number of data transmissions is the highest for the *Per* approach, which as well exhibits the lowest energy budget at the end of the transport compared to the other approaches. This emphasizes the basic assumption that energy expenditure to realize additional computations, either for only evaluating given business rules or for more sophisticated computations like data forecasting and value of information determination as within our approach, is usually beneficial compared to simply transmitting data regularly without assessing it.

Comparing the evaluation results for our multi-stage filtering approach to the results for the *BR* approach, distinct advantages concerning both the number of data transmissions and the remaining energy after the end of the transport processes, could be detected. As can be seen in the evaluation results, these advantages are independent from the forecasting method employed in our approach and reach savings of 36.29% for *RealTrace1*, respectively 25.78% to 27.49% for *RealTrace2*, with regard to the number of data transmissions and over 900J for *RealTrace1*, respectively over 700J for *RealTrace1* with regard to the remaining energy budget. In this context, the computation of the damage inflicted by a threshold violation on the transported goods on the basis of the integral over extent and duration of threshold violation is benefically exploited. For example the detection of the complete loss of the transport goods due to a huge and long lasting threshold violation, as around a transport time of 80 hours within *RealTrace2*, is detected within our approach. Correspondingly, the measurement activities are stopped. This leads to refraining from further data transmissions after this point in time.

With regard to the employed data forecasting methods, different conclusions can be drawn. First of all, by analyzing the results for *RealTrace1*, it can be seen that the computational overhead of all three forecasting methods is very low. As against the background of this temperature trace, 3,325 data transmissions have been initiated independently of the employed forecasting method, the difference in the remaining energy budget after the end of the transport can consequently be attributed to the energy consumption for the different computations to be conducted for the employed forecasting methods. In this context, we could detect that LR and SES computation both consume only 0.22J more energy over the simulated transport time than not making use of any forecasting method. Even DES consumes only 1.92J more energy over the simulated transport time than not using any forecasting method. And secondly, again against the background of the obtained results for *RealTrace1*, it can

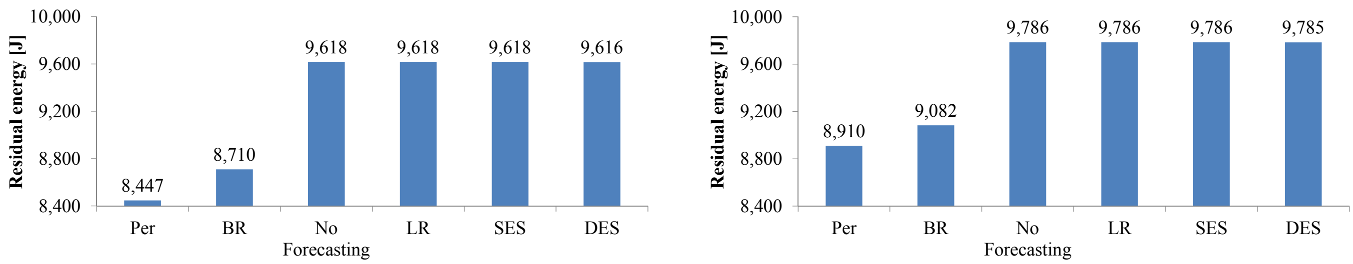
TABLE III: Parameter settings for simulations

α	β	ML	RU	VC	DT	D	WD	PS	TS	M_0
0.7	0.3	100	100	0	0	100	1	0	0	100
CL	NO	$i-g$	$\Delta P + CP + \Delta RC$	PT	EnB	EnC	$ComB$	CB	CC	$ComC$
0.01	52	1	20	RealTrace1: 171 RealTrace2: 120	10000	18.24	10000	10000	2	3



(a) Results for RealTrace1 (b) Results for RealTrace2

Fig. 4: Cumulative packet transmissions after simulated transports



(a) Results for RealTrace1 (b) Results for RealTrace2

Fig. 5: Remaining energy budget after simulated transports

be seen that forecasting possesses no effect in this case on the number of data transmissions, because this temperature trace exhibits rather abrupt threshold violations, but only a small number of these, which makes them hard to predict with the forecasting methods and therefore no earlier warning than without employing forecasting is realized in this case.

With regard to the results of *RealTrace2*, another consequence for employing forecasting methods becomes clear, as all three forecasting methods lead to a higher number of data transmissions than employing no forecasting method at all, in this case. This indicates that the usage of forecasting constitutes a rather conservative data interpretation, which leads to more user notifications as without forecasting. This becomes relevant in *RealTrace2*, because in this temperature trace an oscillating temperature behavior around the upper temperature bound is prevalent. This oscillating behavior leads to more (and earlier) user notifications, because with the forecasting the next threshold violation is already anticipated some time before it really occurs and thus a rather early warning of the user is initiated.

Overall, we can deduce from our simulations that spending computation time and according energy is beneficial in the considered scenario to reduce the number of data transmissions compared to a computationally very lightweight monitoring approach of periodically sending sensor measurements. Furthermore, the incorporation of a more detailed analysis of data against the background of users' specific information desires within the data filtering decision, as expressed within our two-stage filtering approach and the according user-defined parameters, leads to even more savings on data transmissions and can be realized without too much computational overhead, which consequently leads to energy savings as well, while simultaneously providing users' with less useless data by reducing transmissions to more data specifically according to their needs.

VII. Conclusions and Outlook

Energy efficiency is a fundamental requirement in the domain of WSN technology. With data transmission accounting for the major part of energy consumption, local on-mote data filtering is an opportunity to enhance energy efficiency. As data transmission accounts for the major part of monetary costs in a logistics WSN, local data filtering would also contribute to enhanced monetary efficiency there. Consequently, we presented a filtering approach that uses forecasting and value of information. By employing forecasting, the (potential) criticality of sensor data can be assessed and the data accordingly categorized and initially filtered. A further data assessment is realized by computing the data's value of information with afterwards filtering the data based on comparing this value of information to the transmission costs, which would accrue in case the data is transmitted. Thus, reducing the number of data transmissions is achieved, while still accounting for users' information demands in the filtering decision and consequently providing them with the data they need. Within simulation experiments, it could be seen that the computational overhead of our approach is very small compared to other monitoring approaches currently prevalent in logistics and can thus lead to relevant energy and cost savings compared to these approaches by filtering data, while still providing users with data specifically tailored to their needs.

The focus of the work at hand, has been on local decision making. Thus, only an isolated mote-centric view has been incorporated. Consequently, in a next step we will investigate potential dependencies between motes and how such dependencies and potential data redundancies can be exploited.

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