Embedded intelligent objects in food logistics Technical limits of local decision making

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Abstract. The efficiency of transport monitoring systems in the supply chain of food products can be improved by autonomous control, which means that decentralized intelligent objects have the ability to process information, to render, and to execute decisions. In our example the supervision and data evaluation tasks are distributed in a network of wireless sensors as local decision platforms. The supervision network can also include semi-passive RFID tags. The application of such battery powered embedded devices is limited by the reliability and range of communication as well as by the required energy resources. Autonomous control helps to overcome the first restriction. Communication is reduced and the system is less dependent from unreliable network links, but the power required for calculation increases the total energy consumption. In this paper the communication limitation of passive UHF RFID and active wireless sensors were analyzed by laboratory experiments and field tests in sea containers. Several algorithms for local data evaluation by autonomous control were evaluated on typical target systems for wireless units. Calculation times and the resulting energy consumption were measured and compared with the energy that is required for communication.

Keywords. Wireless sensor networks, decision algorithms, distributed computing

1. Introduction

The supervision of food transportation has to be treated as a special case for the application of autonomous control. Firstly, the necessary temperature monitoring produces a huge amount of data that needs to be processed. Furthermore, the data has to be transferred by wireless communication, which typically operates at 866 MHz for passive UHF RFID or 2.4 GHz for wireless sensor networks. Therefore, the high water content is responsible for the high signal attenuation and communication problems in food products. But on the other hand, if the temperature of each transport unit is traced, it is possible to calculate changes in the product quality or losses in the remaining shelf life. If the delivery to retail stores is planed based on the actual shelf life instead of just a fixed production date, the share of products that fall below the quality acceptance threshold can be reduced (Tsironi et. al. 2008; Jedermann, Edmond and Lang 2008).

The required individual temperature tracing can only be done by sensors inside the goods. First field tests have shown temperature deviations of several degrees Celsius in typical transports. The spatial position of temperature maxima and minima fluctuates for different transports (Jedermann, Moehrke and Lang 2010). The field tests indicate that at least 12 or 20 sensors per container are required to estimate a representation of the spatial temperature profile thoroughly.

But, despite of the high amount of sensor data, the logistical planning process requires only very few compressed information, for example the remaining shelf life of each transport unit. Several algorithms for data analysis and reduction have been developed and tested by our research cluster CRC 637 “Autonomous Cooperating Logistic Processes – A Paradigm Shift and its Limitations” in the recent years. These include not only the calculation of shelf life as a function of temperature deviation, but also the prediction of the future temperature course, identification of faulty sensors, and spatial interpolation for points that are not outfitted with a physical sensor.

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One of the basic ideas of autonomous control is to shift decision processes from a central unit to distributed platforms (Böse and Windt 2007). If the data is processed directly at its point of origin, communication can be dramatically reduced. But how does this approach perform under the boundary conditions of our use case in food transportation?

Typically, the temperature monitoring of a high number of probe points is done by battery powered wireless sensor networks, which results in the first technical limit of the application of autonomous control. The available processing power is restricted by energy resources. A decision algorithm, which is implemented on an individual sensor node, has to compete with the radio chip and the sensor element for the battery power.

Aim of this paper is to evaluate the energy efficiency of decision algorithms on embedded systems and relate it to other factors such as communication and sensor measurement.

But, before doing so, the communication range of active wireless sensors will be considered as the second technical limit of the application of autonomous control. The signal attenuation of water-containing products such as fresh fruits was evaluated during the field tests. A set of about 20 sensor nodes was placed in different trucks and containers as described in section 2. In order to reduce the required energy for communication, the use of passive RFID tags will also be considered. But, our laboratory tests in section 3 showed that passive communication reacts even more sensitively to water-containing products.

The effects of a decentralized implementation of decision algorithms on the total energy balance will be summarized in a final section.

Related work

There has been a lot of effort put in by various research groups in topics related to the remote supervision of food transports, but the outcome has not been linked to an overall system so far. Because of the vast amount of literature only single contributions are highlighted in the following overview.

James et. al. (2006) summarized in a review article several measurements about spatial temperature deviations in trucks and containers and attempts to model the temperature distribution. Biologists have developed models to predict the effect of temperature deviations on the shelf life of numerous types of foods, for example Tijskens (2004). A research group from Athens showed that if deliveries are planned based on the actual shelf life instead of a fixed best before date, losses by decayed food can be reduced by 10% in average (Tsironi et. al. 2008). But their approach has not been integrated into an automated supervision system so far.

Such a supervision system requires that the origin and the transportation history is known for every product. A traceability system can be implemented based on passive RFID tags (Regattieri 2007).

If temperature data should be read out during the transport, wireless sensor networks with a higher transmission range than passive RFID are required. Wireless sensor networks are an active research field, especially after the TelosB sensor node (Crossbow 2005) with the Chipcon CC240 radio, which supports the 802.15.4 communication standard for low-rate wireless personal area networks (IEEE 2006), came in to the market in 2004. Several communication protocols have been developed, which enable forwarding messages over several hops to a base station, see Barrenetxea et. al. (2008) and Demirkol et. al. (2006) for example.

However, wireless sensor networks can only cover the communication inside the means of transportation; typically GPRS, UMTS or a satellite link is used to cover the external communication. A protocol standard for access to sensor networks over the World Wide Web was suggested by the Open Geospatial Consortium (Botts et. al. 2007).

Current approaches focus on data storage and management (Schneider and Kroner 2008), but only rarely on the automated evaluation of temperature data. Although there are several methods for sensor data analysis available, they have been seldom applied to sensor networks or food transportation. These include parameter estimation for non-linear system models (Guo 2004), fault detection and isolation by artificial neuronal networks (Zaknich 2005), and spatial interpolation by the so-called Kriging method (Wackernagel 2003; Walkowski 2008).

The focus of our research is to integrate automated processing of measured transport conditions into intelligent sensors and container systems. The above listed methods for sensor data analysis were adapted to the use-case of food transport supervision and optimized for execution inside wireless sensor networks. There has been only very little research in this area so far: Umer and Tanin. (2010) showed how the statistical dependency of sensor measurements can be calculated in a decentralized way by a network of wireless sensor nodes, which is the

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required information for spatial interpolation by the Kriging method. Furthermore, some commercial data loggers already include a simplified shelf life model (Zweig 2008).

Although the signal attenuation of radio waves by water containing food products turned out as the key problem during our field tests, studies on signal attenuation by food products are hardly found, except for Ruiz-Garcia et. al. (2010) for wireless sensor networks and Clarke et. al. (2006) for passive RFID.

2. Technical limits of active communication inside packed foods

Active communication means that both the sender and the receiver are supplied by their own power source. But, for battery powered wireless devices as in our use case, the energy, and thereby the transmission power, is limited. The TelosB wireless sensor nodes provide a transmission power of 1 mW at 2.4 GHz. Due to the signal attenuation, the sensor data had to be forwarded over multiple hops to the base station. We distributed between 18 and 30 TelosB sensor nodes during our field tests inside a truck or 40 feet sea container in order to reproduce a typical scenario for monitoring of food transports.

Most of the existing protocols for sensor networks solutions focus on the general case with data messages of arbitrary type, size, and direction of transmission. The BananaHop protocol developed by our research group (Jedermann et. al. 2011) is optimized to forward small data packets with temperature and humidity measurements over multiple hops to a base station as required by food transportation supervision. By reducing the scope of operation to this basic task the BananaHop protocol is more energy efficient than the SensorScope protocol (Barrenetxea et. al. 2008). Furthermore, the BananaHop protocol is used as an experimental tool for recording radio signal strength and duration of the active radio period.

Although the raw data transfer rate is 250 kbps (Kbit per second) according to the 802.15.4 protocol specification (IEEE 2006) for 2.4 GHz, the effective rate is typically much lower. The transmission of large data packets over a single point-to-point link can theoretically achieve an effective data transmission rate of 101 kbps (Jennic 2006). If the network can be extended 'Ad-hoc' by new sensors at any point of time, timeslots for sending data have to be negotiated anew in each frame. Certain mechanisms for collision avoidance have to be applied. The common CSMA approach (Carrier sense multiple access, Callaway 2004, page 65) first probes whether the channel is clear. If not, the transfer is delayed for a random period. Control messages to search for routes to the base station require additional channel capacity. Furthermore, the data payload size is rather small in transport supervision scenarios. Only 6 bytes of user data have to be transmitted per frame containing temperature, humidity, and battery voltage measurements. The radio of each sensor has to be powered up for 7.5 seconds per frame in order to send its own measurement data, wait for an acknowledgment and to forward the data of 30 other sensors by the BananaHop protocol. This example shows that the effective data transfer rate of multi-hop protocols can drop to values as low as 0.2 kbps.

The energy consumption for communication was calculated as follows: For sending a single message without acknowledgment the radio has to be powered for 15 ms, requiring 720 µJ per message at the current consumption of 20 mA at the minimal voltage of 2.4 Volts for the TelosB. The radio draws almost the same current in receive mode, but because the exact point of time when the message arrives is unknown, the radio has to be powered for an extended period, typically 100 ms, which sums up to a total energy of 5.5 mJ for receive and transmit. The radio-up period of the BananaHop protocol in the example above results in an average energy consumption of 360 mJ per frame to transmit one sensor message including overhead for forwarding. The network can operate for 7000 measurement and communication cycles with a typical battery capacity of 3000 mAh per sensor.

The implementation of the external communication either by GPRS/UMTS or over a satellite link is handled in a separate paper (Becker el. al. 2010).

Experimental data losses

The application of wireless sensor networks is not only restricted by energy and effective data transfer rate, but most crucially by the communication range, especially if the radio wave propagation is hindered by water-containing products. The radio link quality and the performance of the BananaHop protocol was tested under the

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conditions of real transports in 2009 and 2010. The field tests were supported by Dole Fresh Fruit, Cargobull Telematics, and Rungis Express as partners of a transfer project of our research cluster CRC 637. Four separate experiments were carried out in order to analyse the conditions during different parts of the logistic chain, such as short distance truck delivery, long distance sea transportation, and processes inside a warehouse.

1. During the first experiment 20 sensors were installed at the inner walls of a refrigerated truck. Frozen fish and chilled fish products were loaded in two separate compartments. The truck was only partly filled, leaving a free airspace of about 1.5 meters above the products. The products were stored inside the truck over the weekend and then delivered to a nearby customer in Bremen, Germany. Only the packet rate of single links was recorded during this first experiment, the full protocol implementation was not yet available. But an analysis of the link data showed that each sensor in each frame had several alternatives to contact the base station either directly or by forwarding over one additional hop.
2. The truck in the second experiment was split in 3 compartments for different temperature zones. Boxes with frozen meat, chilled fish, and vegetables were stacked at the walls. A corridor in middle of the truck was left empty. The goods were delivered from a distribution centre in the outskirts of Berlin to several customers in the city centre. The whole tour including the return to the distribution centre took 8 hours.
3. A third test was carried out inside a banana ripening room at a warehouse close to Hamburg. The sensors were packed in the corners of banana boxes. The boxes with sensors were placed in the centre of the pallets. Ten pallets were loaded into one row of the ripening room. Temperature and link packet rates were recorded over 3 days.
4. The fourth experiment was carried out during 2 weeks of sea transportation of bananas inside a 40 feet refrigerated container from Costa Rica to Hamburg. The densely packed container left only a little free airspace below and above the pallets of 10 cm height.

Table 1 gives a summary of the 4 experiments, showing large variations in the percentage of sensor data packets that were not forwarded to the base station (**Loss-Rate**) and the number of required hops (**Max-Hops**).

Table 1. Summary of experiments with BananaHop protocol

Experimental setup	Date	Number of Sensors	Distance between sensors	Sensor mounting	Max-Hops	Loss-Rate
1. Truck, partly filled with fish	April 2009	20	1 … 4 m	14 at walls, 6 inside freight	2	0 %
2. Truck partly filled (mixed load)	March 2010	30	1 ... 2 m	At walls	2	1.3 %
3. Banana ripening room	July 2009	18	0.25 … 0.5 m	Inside corner of boxes	5	0.5 %
4. Bananacontainer, densely packed	Sep. 2009	20	0.5 m	Inside centre of boxes	5	24 %

The truck tests with a lot of free airspace between the sensors were rather uncritical. At maximum 1.3 % of the data messages were lost in one experiment. Three quarters of the sensor nodes could directly send to the base station (1 Hop). The data from the remaining sensors had to be forwarded over one additional sensor (2 Hops).

However, if the sensor nodes were packed inside pallets, the data had to be forwarded over up to 5 hops. The experiment in the ripening room showed almost no problems concerning the Loss-Rate. But, inside the packed sea container the Loss-Rate rose to an unacceptable value of 24%. Although the sea container experiment was also the test with the longest duration of two weeks, the length of the experiment cannot be held responsible for the high Loss-Rate. Even if only the first two days of the sea container experiment are considered, the loss rate is with 19% much higher as in the truck and banana ripening room tests. The high Loss-Rate is rather caused by the limited free air space inside the loaded container and by the different positions of the sensor nodes inside the boxes. Due

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to packing, a little free airspace is left in the corners of the boxes, which creates an empty channel in a vertical stack of boxes. The sensors in the ripening room experiment could communicate through this channel, whereas the sensors in the sea container experiment were packed in the centre of the boxes without any free airspace surrounding them.

Unfortunately, the last experiment with the highest Loss-Rate is the one that is closest to real-world application. Long distance transports are the most critical for quality degradation, and therefore, the first candidate for sensor supervision. In order to save costs, containers are densely packed. Partly filled trucks are only found in local delivery. Furthermore, the direct core temperature is required for correct quality prediction. Sensors in the corners or close to the surface of the boxes are partly affected by the stream of cooling air resulting in unpredictable behaviour. Tests have shown that small variations in the sensor position can have a large effect on the measured temperature. Some of the sensors mounted close to the surface are mostly affected by the cooling air and cool down with a time constant less than 0.5 days. Others measure rather the fruit temperature and require more than 3 days to cool down.

Analysis of signal attenuation in banana sea containers

Therefore, the last experiment should be analyzed in more detail. The packet rate was not considered for the network as a whole, but for the direct links between pairs of sensors. The average packet rate of the 12 links with a distance of 0.5 meters was 52 %. One-third of these links failed completely, another third had temporary dropouts with durations between 8 hours and several days, and the remaining third provided almost stable communication. The BananaHop bypassed some of the missing and poor links by an additional hop, but 24 % of all messages remained undelivered. Part of these failures is due to inappropriate routing by the network protocol. But a further analysis of the recorded link information showed that for 20 % of all messages there is no physical route available from the source sensor to the base station during the relevant time frame. Therefore, an improvement of the BananaHop protocol or the selection of another protocol could decrease the Loss-Rate by 4% only, but it will not solve the general problem. In order to achieve an acceptable Loss-Rate it is necessary to modify the radio hardware instead.

A radio with higher transmission power can be used as the first alternative. The ZigBit Amp OEM Modules from Meshnetics (2008), for example, provide a radio output power of 100 mW, which is 20 dBm higher than that of the TelosB nodes.

The other alternative is to use a radio operating at a lower frequency range, which is less sensitive against signal attenuation by water. The signal attenuation is caused by dielectric losses, which are proportional to the imaginary part of the relative electric permittivity ε_R. Cole and Cole (1941) provided a formula to calculate ε_R as a function of frequency (Equation 1 with $\varepsilon_\infty = 6$, $\varepsilon_0 = 80$, $f_{Reso} = 16$ GHz at room temperature).

$$\varepsilon_R(f) = \varepsilon_\infty + \frac{\varepsilon_0 - \varepsilon_\infty}{1 + j\dfrac{f}{f_{\mathrm{Reso}}}} \tag{1}$$

For typical frequencies between 433 MHz and 2.4 GHz the imaginary part, and thereby the signal attenuation, is almost proportional to the frequency. Therefore, with regard to signal attenuation, a low frequency would be the best choice.

Unfortunately, the selection of the radio carrier frequency is limited to only few ISM (industrial, scientific and medical) radio bands, which are available worldwide or at least in large regions. Large bandwidths are only available at the higher frequencies. For example the ISM band at 2.4 GHz provides a bandwidth of 80 MHz, which can host 16 separate channels for wireless sensor networks with a data rate of 250 kbps each (IEEE 2006). The ISM band at 915 MHz provides only 26 MHz of bandwidth, but this band is only available in the American continent. For Europe the frequency has to be switched to the ISM band at 868 MHz with only 0.6 MHz bandwidth (IEEE 2006). The ISM band 433 MHz is not commonly used for wireless sensor networks because the total bandwidth is restricted to 1.6 MHz and the duty cycle is limited to 10 % (IEEE 2006, Annex F). The energy consumption increases for lower bandwidths because the transmission is slower and the radio has to be powered for a longer period of time.

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3. Limitations of passive RFID communication

Passive communication needs no power source on the side of the tag and thereby overcomes the energy restrictions of active communication. But on the other hand, the restrictions in communication range and data transfer rate are even more severe. These two limitations of passive RFID were tested in laboratory experiments in order to decide whether passive RFID is a useful alternative to active wireless sensor nodes for the temperature supervision of food products.

RFID tags can be combined with a sensor. Such semi-passive RFID tags contain a battery that is only used to power the sensor and to store the measured values in non-volatile memory. The communication is still passive, meaning that the required energy is provided by the electro-magnetic field of the reader. The reader receives the reflected signal from the tag. Because the radio wave has to cover two times the distance between reader and tag, the signal strength decreases with the fourth power of the distance, not with the second power as in active communication.

The experiments were carried out with EPC Generation 2 Tags in the UHF frequency range of 866 MHz. The EPC standard is recommended by the major food retailers. Furthermore, it offers the highest data bandwidth.

The signal attenuation by water bottles was tested during the first experiment. Eight tags were placed on the surface of the stack of water bottles and 11 tags behind the first, second, and third rows of bottles (**Figure 1**, Jedermann et. al. 2008). Reliable identification was possible for the surface tags with a minimum reader power of 200 mW. Tags after the first row required 500 mW of reader power to achieve 100% identification rate. But the tags after the second row achieved only an identification rate of 50%, even at the maximum reader power of 1 Watt. The high sensitivity of passive RFID against water is also supported by other studies. Clarke et. al. (2006) observed a reading rate of 97 % in a pallet with empty bottles. But, when the bottles were filled with water the reading rate dropped to 0.8 %.

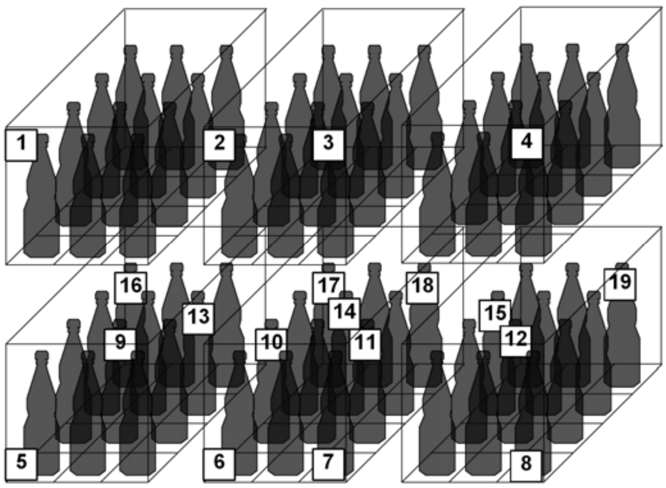

Fig. 1. Position of tags at surface of boxes and at bottle necks.

The reading of RFID tags that are packed inside a container is completely infeasible. Wireless RFID readers can also not be applied for continuous transport supervision. Typically, the RFID reader modules consume between 2 to 30 Watts. The only practical solution is to read the tags during the loading or unloading of the container. Tags should be mounted to the surface of the product; even 10 cm of water-containing material can reduce the identification rate to an unacceptable value.

If the container is loaded by a fork lift, the data transfer rate becomes a critical factor. The tags are only visible for a short period for the reader antennas. The second experiment was carried out with a pallet of beer bottles placed on a foil wrapper machine. The machine operated at its maximum speed of 10 rotations per minute equivalent to an angular velocity of 2.2 km/h. Bulk identification was not problematic; each of the 10 tags at the surface of the pallet could be read at least 29 times per rotation. **Figure 2** shows the time window for

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identification. For 1.4 seconds, more than 90 % of the tags could be identified at the maximum reader power. The length of this window, during which the tags are visible to the reader, was compared with the measured data transfer time for different operations in **Table 2**. The time to read 1 Kbyte of data, equivalent to 700 temperature values with a resolution of 12 bits, could only be estimated based on a projection of the protocol specification, because the semi-passive sensor tags were not available in 2008 when the experiment was carried out.

Table 2. RFID data transfer time for different operations

Operation	Experiment	Data transfer time
Identification of 4 tags	Water bottles, static	43 ms
Reading of 28 data bytes	Water bottles, static	22 ms
Reading of 1 Kbyte temperature data	Simulation	172 ms
Writing of 28 data bytes	Water bottles, static	197 ms
Writing of 28 data bytes	Rotating pallet	267 ms

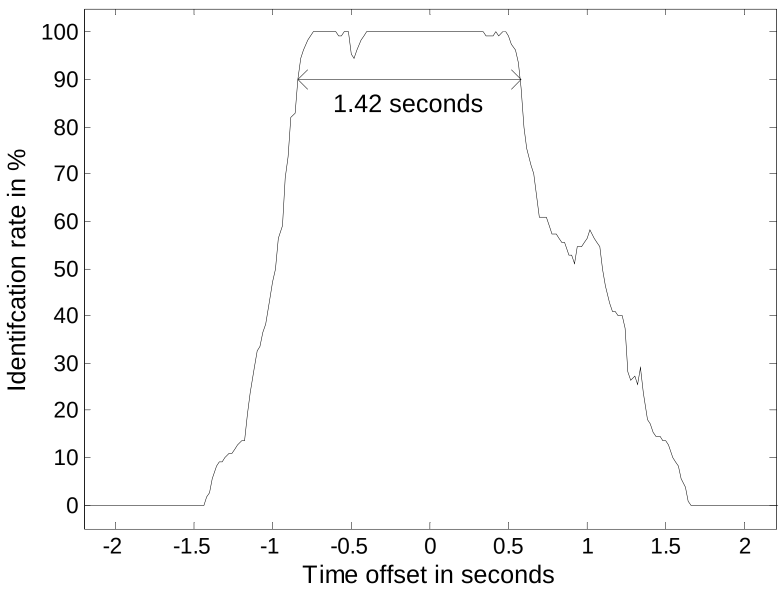

Fig. 2. Time window for identification measured on a fail wrapper machine

Seven tags each with 1 Kbyte of memory can be identified and read out during one rotation under optimal conditions. But this rate can hardly be achieved for the reading of sensor tags by a RFID gate during the unloading of a container. Fork lifts typically move faster than the angular speed of only 2.2 km/h as in our experiment. Communication is often distorted and data frames have to be repeated.

For this reason we dropped the idea of reading out the full temperature history from semi passive sensor tags. But, the use of low cost RFID technology can become an option if data processing is integrated into the tag. If only the remaining shelf life and the maximum temperature have to be transmitted, a multitude of tags could be read during the unloading and the low data transfer rate would not be an obstacle. This idea of autonomous control on RFID level assumes that tags with programmable micro controller are available, which unfortunately is not the case yet. Therefore, we currently use passive RFID tags only for identification in our project.

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4. Required processor energy for decision making

Poor radio links can be compensated by repeated transmissions, but this further increases the energy required for communication. The most promising way to reduce the total energy consumption is to minimize the number of data messages by intelligent algorithms that decide which data contains only just redundant information and which contains crucial new information for the logistic planning process. Only the summarized data, the calculated effects of sensor deviations and sensor failure state information, are transmitted instead of the complete measurement data set. But the decision, which data is crucial and which not, needs processing time on the embedded system and thereby energy as well. In order to evaluate the advantages of local decision making, the required energy in (milli) **Joule per Decision** was evaluated for different example algorithms.

However, it is hard to decide whether a local implementation of the algorithm is useful, if only the bare value for energy consumption is known. First of all, the considered algorithms bring clear advantages on their own, independent from their location of the CPU platform, either central or distributed in the network. They perform sensor data evaluation tasks that had to be done manually in the past or have not been done at all. Only with automated processing tools it is possible to carefully analyze the temperature data of 20 sensors from each container.

Secondly, it is hardly feasible to directly compare the algorithms because they have different objectives. Two of them predict quality changes or the future temperature development. Two other algorithms for detection of faulty sensors by plausibility checking also have different capabilities: The first focuses on slowly increasing tolerances, and the second one is good in detection of sudden offsets that only affect a single sensor.

Finally, the algorithms are executed on different system layers. Some process the data of single sensors; others combine the data of sensor clusters or group of neighbouring sensors, and the rest process the data of the whole container. Some need only one time initialization at the beginning of the transport and only very few resources to process the data in the following steps. Others are programmed in an incremental form and need almost no initialization.

The following section evaluates the advantages of a decentralized local implementation versus a central implementation with regard to energy consumption. Because the required processing power of most algorithms exceeds the capabilities of the TelosB platform, the iMote2 wireless sensor node from Crossbow (2007) was introduced as alternate hardware platform. It uses the same CC2420 radio chip as the TelosB, but provides an ARM XScale processor with much higher computation recourses, but also higher energy consumption. The ARM processor allows the use of more elaborated programming languages as ‘C#’ and ‘Java’ and complex mathematical operations such as large matrix inversions. The TelosB sensors were programmed in ‘NesC’, which is a special dialect of the ‘C’ programming language. The differences between the two wireless platforms and typical values for supply voltage and clock rate are summarized in **Table 3**.

Table 3. Energy properties of applied wireless sensor nodes.

Sensor node	TelosB	iMote2
Processor	MSP430	ARM XScale
RAM	10 Kbyte	32 Mbyte
Flash	48 Kbyte	32 Mbyte
Typical clock rate	4 MHz	416 MHz
Typical supply Voltage	2.4 Volt	3.6 Volt
CPU current (difference between active and idle CPU)	1.5 mA	50 mA
Energy per second of calculation	3,6 mJ	180 mJ

The applied algorithms are briefly introduced before the experimental results of the required CPU times are presented.

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Estimation of temperature related effects on shelf life

In general, the effect of temperature deviations on the quality of foods is of more importance than the temperature itself for the supervision of chilled food transports. The so-called shelf life models (Jedermann, Edmond and Lang 2008) were applied to calculate the remaining quality as a function of the temperature history. The considered model applies two Arrhenius type equations to model the temperature dependency of bio-chemical aging and decay processes. The algorithm was programmed in an incremental form, only two exponential functions and two divisions have to be calculated after each temperature measurement.

So far, the shelf life model is the only algorithm that has been implemented on the TelosB platform. First tests were carried out in 2008 (Jedermann, Edmond and Lang 2008). Integer operations with 16 or 32 bit were used instead of floating points for faster execution. The average error of integer implementation compared to double precision floating point calculation is about 0.5 %. The results were compared with a floating point implementation on the iMote2 platform for the current study.

Only the resulting remaining shelf life has to be read out at the end of transport instead of transmission of the full temperature history. Alternatively, the system can send a warning message if the shelf life drops below a critical threshold. If the shelf life and the temperature are in range, no communication is necessary at all.

Prediction of temperature development

The future temperature values inside the container can be calculated by using system identification techniques, which estimate the missing parameters for a given model structure. Online recursive methods require much lower resources in terms of memory and CPU power than offline counterparts, and they are easier to implement on embedded platforms. It is also of paramount importance to have lower order matrix dimensions. The Feedback-Hammerstein parameter adaptation algorithm was implemented on the iMote2 platform (Palafox-Albarrán 2010). The advantage of the Feedback-Hammerstein is that it can also estimate parameters of non-linear effects such as the thermal energy generated by the ripening of the bananas as a function of temperature. Furthermore, it does not need any matrix inversion. In total, 3 parameters are estimated and updated after each measurement. In order to give an accurate prediction, the model parameters have to be iterated over 3 days at a measurement interval of 1 hour, equivalent to 72 cycles. The 3 model parameters were transmitted to the transport operator after this training period. Further communication is only required if the measured temperature deviates from the model prediction. The corrected model parameters and the current temperature have to be retransmitted in this case.

Spatial interpolation by Kriging

Methods to estimate the temperature in points of space as a function of the neighbouring measurements bring further benefits. An estimation of temperature can be necessary for some points because that particular point has no physical sensor at all, the sensor is currently turned off to save energy, or the sensor is unreliable due to faulty measurements. In general, this problem is solved by spatial interpolation. The Kriging method (Jedermann and Lang 2009) provides an accurate estimation, which is better than simple methods like inverse distance weighting. The measurements of the given sensors (source points) are multiplied with weighting factors to ascertain the temperature in destination points that are not allocated with sensors. The first step of Kriging is to calculate the weighting matrix. It is then applied to the current measurements in the second step. In general, the coefficients of the weighting matrix have to be calculated only once for each type of transport. The weighting matrix has only to be re-calculated if the loading scheme is modified and the temperature dependency between points change due to changed air streams. A further advantage of the Kriging method is that it can evaluate its own accuracy by calculation of the so-called Kriging Variance as the average error of prediction of the interpolated temperatures (Walkowski 2008).

The Kriging method does not work on the level of single sensors as the previous algorithms, but for groups of sensors. In the first test scenario, the Kriging method was implemented on one iMote2 sensor node in order to

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predict the temperature in 20 destination points by the measurements of 20 source points. Compared to a network that queries all 40 sensors, half of the sensors can be powered down for saving energy. The decision, which sensors should be turned off, can be based on a calculation of the Kriging Variance for their spatial locations. Those with a low Kriging Variance value should have the lowest approximation error for a spatial prediction. But so far, this selection process is not yet automated.

Autonomous plausibility checking

The risk to draw wrong conclusion due to erroneous measurements increases with the size of the network. Sensors might be faulty because of low battery voltage, mechanical damage, or drifts by aging. Therefore, it is essential to evaluate the reliability of the sensor records. Any abnormality in a wireless sensor network needs to be detected, isolated, and investigated. The measurements of one sensor can be denoted as plausible, partially plausible, partially implausible, or implausible. The deviation can be caused either by a sensor fault or a transport disorder such as unreported opening of the container doors.

Plausibility checking needs in general full access to the measurement history. If an autonomous transport monitoring system sends only compressed sensor data such as calculated shelf life and model parameters to the transport operator, the algorithm for plausibility checking also needs to be implemented locally.

Two different approaches for plausibility checking in transport supervision were developed by our group. Both compare a prediction for a particular point with the actual measurement at the same location. But, they differ in the way how the prediction is calculated and by their ability to detect different classes of sensor faults.

The Kriging method was modified to detect sensors with high tolerances. The actual measurement of each sensor was compared with a spatial interpolation of the remaining 39 sensors in our test scenario. If the residuum between measurement and prediction exceeds the error that should be expected according to the Kriging Variance by a certain factor, a warning message is triggered. The Kriging method detects when a measurement deviates from the typical spatial profile of the temperature distribution. Kriging is well suited to detect high sensor tolerances and slowly increasing offsets. But this approach can only reduce the external communication of the container, not the internal one of the sensor network, because the data of all available sensors are required to calculate the prediction.

Artificial neuronal networks for plausibility checking

Artificial neural network (**ANN**) is a knowledge based technique including nonlinear mapping features and generalization which makes it a favourite for model-free data processing (Zaknich 2005).

A plausibility test for clusters of 4 sensors each was implemented by a multi-layer perceptron ANN network (Jabbari et. al. 2009). The value for the sensor undergoing the test is predicted based on its own last measurement and the current measurements of its 3 neighbours. The network consists of two hidden layers with 4 neurons each and an output layer that sums up the weighted data. Using two hidden layers increases the nonlinear mapping feature between the input pattern and the target. This ANN approach is the best choice to detect sudden changes, for example, by a mechanical damage of the sensor element, battery failure, or intrusion of warm air though an open door. But, slowly increasing offsets cannot be detected because the network simply adapts to it.

The weighting factors of the ANN are trained by a modified backpropagation technique. To overcome the memory and processing constraints, the entire network can be updated continuously for training and data approximation solely by using a limited number of neurons and samples, which is called sliding backpropagation (Jabbari et. al. 2009). The new algorithm deals with the limitations of wireless sensor nodes in data approximation by using a simplified network. Therefore, the new algorithm is an efficient solution in terms of calculation time and memory size compared to the traditional backpropagation technique. The energy consumption of the sliding backpropagation technique is adjustable by the determination of network architecture, training parameters, and the desired data approximation accuracy. The backpropagation is repeated until the output error drops below a training threshold. The tests were carried out with a medium setting of 0.1 °C. A setting for higher accuracy of 0.001 °C requires 3 times more CPU resources.

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The required classification of different fault scenarios is handled by a second ANN. A probabilistic radial basis function (RBF) network can discern between internal sensor faults and external influences (Jabbari et. al. 2010).

The ANN plausibility testing was implemented under the .Net Micro Framework with C# on the iMote2 sensor nodes and not under Linux with Java as with the other algorithms. The .Net Micro Framework allows only a fixed clock frequency of 104 MHz. The reduced CPU power consumption was considered in the following calculations. Another contribution from our group by Wang et. al. (2010) showed that it is also feasible to implement an ANN on the TelosB platform. Sliding backpropagation training for a network with 4 input neurons can be executed in 162 ms on a TelosB node per step. But, those results could not directly be compared because its ANN structure differs from the one that was used for plausibility checking.

Dynamic combination of algorithms

So far, the presented algorithms for autonomous sensor data evaluation were handled separately. But in many application scenarios it would be beneficial to combine two or more of these processes. For example, shelf life prediction and plausibility checking can be combined. Furthermore, if the system detects a faulty sensor by plausibility checking it can apply a third algorithm to replace the missing sensor value by a spatial interpolation.

Because it is not known in advance which of the algorithms are required and permanently running, all algorithms create a high overhead; a highly developed system should be able to execute and integrate a number of algorithms only on demand. The system should also provide for the case that the user wants to update an existing algorithm with a new software version or wants to install a new type of data evaluation method.

The JAVA based OSGi framework (formerly Open Source Gateway Initiative) was installed on the iMote2 to enable such features (Wessels et. al. 2010). OSGi can update and install the so-called software bundles during runtime without interrupting the execution of the remainder of the system. Except for the ANN based plausibility checking all algorithms are available as OSGi software bundles. Once started, the OSGi framework requires only a little CPU time. Only the installation of new bundles, which takes in average 470 ms of CPU time, has to be taken into consideration.

5. Measurement of required CPU time

The required CPU time for the execution of the described algorithms was measured in laboratory experiments. A digital output pin was programmed to toggle after each model step on the TelosB nodes. The time per incremental model update was measured with an oscilloscope. Timing measurements on the iMote2 nodes were carried out by making use of the system clock. The results are summarized in **Table 4**. CPU times for initialization and incremental update are listed separately. The table also lists the energy consumption for an example scenario where the algorithm is initialized and runs for 50 measurement cycles. For the algorithms, which require spatial data, a setup with 40 sensors distributed on the walls of a delivery truck was considered. Two complete data sets were available from tests in cooperation with a German food provider for hotels and restaurants (Jedermann and Lang 2009). The required energy was divided by the number of input sensors for easier comparison.

Further energy consumers

The measured values for energy consumption of different algorithms have to be compared with other energy consumers and battery capacity in order to say whether the performance of local decision making is acceptable or not.

The sensor measurements were rather uncritical. A typical combined temperature and humidity sensor such as the SHT75 from Sensirion requires only 0.1 mJ per measurement. Only gas sensors cause energy problems because the detector element has to be heated for at least one minute to several hundred degrees Celsius. An example calculation for the AS-MLK sensor for methane from Applied Sensors resulted in an energy consumption of 4500 mJ per measurement.

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Table 4. Comparison of decision algorithms.

Algorithm	Shelf life	Shelf life	Temperature prediction
Platform / Programming Language	TelosB / NesC (integer)	iMote2 / Java (OSGi)	iMote2 / Java (OSGi)
Code size	0.9 Kbyte	7.3 Kbyte	8.4 Kbyte
Number of input sensors per instance	1	1	1
CPU time for initialization	-	-	72 steps initial training 360 ms
Incremental operation and CPU time per step	Update shelf life 0.96 ms	Update shelf life 0.58 ms	Update model parameters 5 ms
Energy for processing 50 sampling intervals including initialization per input sensor	0.17 mJ	5 mJ	110 mJ
Reduced communication	Only warning for unexpected drop of shelf life	Only warning for unexpected drop of shelf life	Only model parameters instead of full temperature history

The stand-by current of the two hardware platforms also has to be considered. The TelosB sensor requires only 1 µA when no communication, measurement, or calculation tasks are carried out. But unfortunately, the Linux operating system for the iMote2 does not support low-power deep sleep modes of the ARM processor. The clock frequency can only be switched down to 104 MHz, which still requires a supply current of 55 mA. Before the iMote2 can be applied on transports over several days or weeks, the operating system has to be extended. A low power mode, which halts the CPU but continues to periodically refresh the volatile memory, would require about 1 mA. The energy consumers and the battery capacity are summarized in **Table 5**.

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Table 4. Continued

Algorithm	Spatial interpolation by Kriging	Plausibility testing by Kriging	Plausibility testing by ANN
Platform / Programming Language	iMote2 / Java (OSGi)	iMote2 / Java (OSGi)	iMote2 (104 MHz) / C#
Code size	40.3 Kbyte	40.3 Kbyte	8.4 Kbyte
Number of input sensors per instance	20	40	4
CPU time for initialization	Calculation of weighting matrix 2189 ms	Calculation of weighting matrix 58500 ms	-
Incremental operation and CPU time per step	Application of matrix 17.5 ms	Application of matrix 70 ms	Back propagation Training 770 ms
Energy for processing 50 sampling intervals including initialization per input sensor	28 mJ	279 mJ	860 mJ
Reduced communication	About 50% of the sensors can be turned off	Only external communication reduced	Communication restricted to small clusters

Table 5. Summary of energy consumption

Operation	Required energy
Sending 50 messages (single direct link transmit and receive / including multi-hop overhead)	275 mJ / 18000 mJ
Decision algorithms (for 50 measurement intervals/one sensor)	0.17 mJ … 860 mJ
Measure temperature and humidity 50 times	5 mJ
One gas measurement	4500 mJ
Installation of new OSGi Bundle	85 mJ
Standby one day (TelosB/iMote2)	207 mJ / 17 100 000 mJ
Battery capacity (TelosB with 2*AA /iMote2 with 3*AAA)	25 500 000 mJ / 11 650 000 mJ

Calculation versus communication energy

From an energy point of view, the local decision making algorithms can only be advantageous if the amount of communication is reduced. The reduction of the number of temperature or humidity measurements brings limited benefits only. In the following the total energy for 50 sample intervals was considered in order to attain a fair comparison between algorithms with and without initialization. The algorithms are first compared with a direct

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send-receive link without the need for collision avoidance, acknowledgment and other protocol overhead. Such a direct link requires 275 mJ to transmit and receive 50 sensor messages. The resulting energy consumptions are summarized in **Figure 3**.

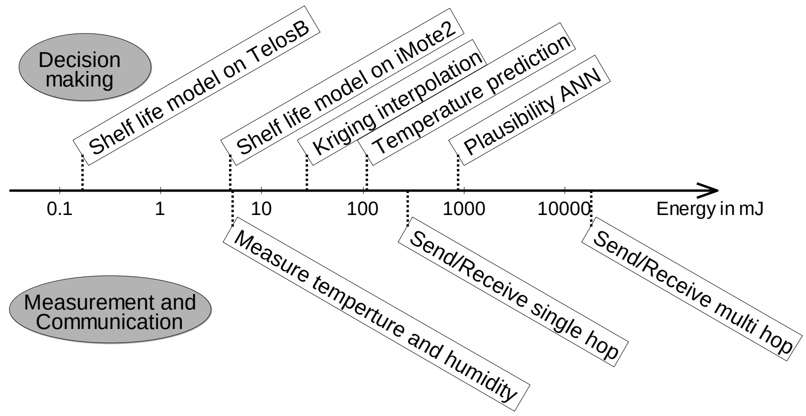

Fig. 3. Comparison of energy consumption for 50 intervals

The shelf life algorithm showed the best performance and the clearest case for local implementation of decision algorithms. The calculation of 50 model steps takes much less energy (0.17 mJ / 5 mJ) on both the hardware platforms than sending the same number of sensor messages over a direct link. The shelf life algorithm would break even if the amount of transferred data is cut down by only 1 message, but in fact the communication is almost reduced to zero because only occasional configuration and warning messages have to be sent. The algorithm could run even with the thin-film battery of semi-passive RFID tags (Jedermann, Edmond and Lang 2008).

The implementation on the TelosB was 30 times more energy efficient than that on the iMote2. This is partly due to the fact that integer instead of floating point arithmetic was used for TelosB. But, even a floating point implementation on the TelosB requires 6 times less energy per model step than on the iMote2. The MSP430 processor of the TelosB platform provides the best energy efficiency, but unfortunately it is unable to handle more complex algorithms such as Kriging due to memory restrictions.

The local implementation of the model based temperature prediction also gives clear advantages compared to a central solution. After the initial training phase the communication is reduced to occasional parameter updates. The required energy for 50 model steps (110 mJ) is also lower than sending the full temperature data set over a direct link.

The Kriging method for spatial interpolation needs much larger amount of energy for the initial calculation of the weighting matrix. But after initialization, the Kriging method replaces the measurements of 20 sensors, not only 1 as in the previous examples. The related energy consumption per input sensor (28 mJ) is much lower than the saved energy for sensors that can be turned off (275 mJ per sensor).

The case for the two plausibility checking methods is a bit more complicated. The plausibility checking by Kriging reduces only the external communication, which is a benefit on its own in regard to the costs of satellite or mobile data transfer tariffs, but this cannot be compared to energy costs. Umer and Tanin (2010) suggested a distributed implementation of Kriging. The weighting matrix does not take the whole network as input, but only 5 to 10 neighbour sensors. If the matrices are calculated by dedicated sensor nodes inside the network, the internal communication of the sensor network could be reduced as well.

The ANN based plausibility checking needs the highest computation resources (860 mJ) per sensor, but it also includes a method for classification of different fault types. Other as the Kriging method, the ANN based approach is well suited for an implementation within the network. Only 4 sensors of a cluster instead of all 40 have to send their data to a cluster head, which carries out the plausibility checking. The communication of the wireless sensor network can be reduced by 90% in the test scenario.

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Under the optimistic assumption of a network that consists only of direct links, a distributed implementation of the ANN brings no energy advantages. But the protocol overhead cannot be neglected in a real wireless sensor network. If the energy consumption of the BananaHop protocol is taken as reference (18000 mJ), the calculation of the sliding backpropagation requires only 5% of the saved communication energy.

6. Summary and conclusions

The spatial supervision of temperature and other sensor parameters of transports of perishable goods create a high data volume that is difficult to handle manually. Several automated algorithms for sensor data processing were introduced, which not only summarize the sensor data but also provide additional types of information such as the calculated remaining shelf life or indication of faulty sensors. Because the two suggested methods for plausibility checking have different focuses, it is recommended to implement both of them in order to detect slow increasing tolerances as well as sudden offsets by malfunction of the sensors or external influences.

The methods for automated sensor data processing can be implemented either centrally on a server in the office of the transport operator or locally, directly on the sensor nodes or a processing platform inside the means of transportation. But before the local implementation can come into practice, two technical problems have to be solved: Firstly, the high signal attenuation by water-containing products has to be compensated by adapted radio hardware; secondly, the operating system for the iMote2 has to be extended to support low-power sleep modes in order to reduce the stand-by current.

The measurements of the required CPU times showed that it is feasible to run the algorithms on low-power embedded systems. Decisions can be made at the hardware platform where the input data has its spatial origin. This is especially the case for the temperature supervision of perishable products with a high volume of distributed sensor data. On the other hand, the transport planning of ‘dry’ goods without sensor supervision mainly requires data, which do not origin from the truck or container such as new orders and traffic information.

The distributed implementation of sensor data processing mainly brings advantages for the case of perishable goods. The communication volume is reduced, thereby the energy is saved and the system becomes less dependent from communication failures.

The methods for shelf life calculation, temperature prediction, and Kriging interpolation save more energy than they require for computation, even under the optimistic assumption that the sensor network can run without any protocol overhead. The case for more complex algorithms for plausibility checking depends on the external communication costs and the internal protocol type. But an energy comparison with typical multi-hop protocols also shows clear benefits.

The suggested algorithms can run on the CPU of typical sensor nodes without hardware extensions. If the installation of a wireless sensor network for spatial transport supervision is planned, it is recommended to extend the sensor node software for autonomous data processing concurrently.

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