Comparison of Energy-Efficient Sampling Methods for WSNs in Building Automation Scenarios

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Abstract

Energy efficiency is an elementary requirement for battery-operated wireless sensor networks. Fulfilling this requirement concerns not only the device hardware and communication protocols, but also the device applications. Adaptive sampling approaches allow reducing the number of messages and can therefore be very relevant for sensor networks. This paper evaluates this relevance for different adaptive sampling approaches in two realistic closed control loop scenarios from building automation.

1. Introduction

Home- and building automation is often mentioned as a future mass-market application for wireless sensor networks (WSNs). From the view point of WSNs, it is attractive for different reasons [1, 6, 15]. First, networks are rather large, containing up to thousands of devices. Second, networks often base on decentralized processing. Third, devices fulfil very heterogeneous tasks. Also, the domain of home and building automation looks promising on wireless technologies [3, 15], primarily due to their easy installation without wiring. Therefore, WSNs support flexible room usage scenarios, where walls can be flexible moved to adjust to new layouts. Devices can be installed where no wire can be used like on fashionable glass walls or in historic monuments. This addresses the most important scenario, namely the retrofitting of building automation to existing buildings. This market covers already most contracts today and will further grow, as building automation permits energy management in times of rising energy prices.

However, building automation is also a conservative automation domain. As the systems have to work reliable for 10 to 30 years with a warranty by the system integrators, they are not very experimental with new technologies. Hence, WSNs have to fulfil existing requirements of this domain, such as a reliable message transmission and real-time requirements down to 100 milliseconds for closed control cycles for illumination or ventilation. On the other hand, requested battery lifetime starts at 5 years [3, 15]. This is understandable if one considers maintenance of a office building with 1200 devices installed. Then one battery needs to be changed in mean per day, which often requires opening suspended walls or ceilings and interrupting office work. Neither the facility manager nor the office owner are very fond of such a laborious task.

Thanks to the significant research of the last years, WSNs can fulfill the requirements of the domain. Energy-efficient hardware and operating systems [4, 13] permit a runtime of several years. Developed communication protocols [5] take advantage of these mechanisms providing runtime and real-time requirements. However, while node hardware continuously shrinks in size, batteries stay large and prevent small form factor devices. Alternative energy harvesting approaches require space as well. Hence, shrinkage of sensor devices requires a reduction of energy capacity and device power consumption.

However, latency and energy efficiency create a trade-off [2, 5] with practically relevant compromises not easy to reach. WSN devices save energy by deactivating parts of their hardware (sleep modes) and try to spend as much time as possible in a deep sleep mode, in which only a timer ensures the wake-up. Thus, a device with long sleep intervals has low energy consumption but long latency. The optimum of this trade-off is mainly defined by the processing and communication requirements of each individual device and the protocols coordinating the communication between several devices.

Common wireless solutions in building automation like Z-Wave and EnOcean [15] approach this trade-off at the moment by using simple single-hop star architectures, in which several battery-supported sensors connect to a full-functional wired base station that is always available. Hence, sensors can use simple CSMA protocols to connect to the base station anytime and go to sleep very fast, rendering the approach simple and energy-efficient. Well-known problems of CSMA protocols, namely the hidden-terminal-problem, the probability of collisions and the unbound delays, are avoided by a low message rate.

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IEEE 802.15.4 [1] and many other protocol developments [5] provide a higher flexibility and more complex mesh-network topologies but have a higher protocol and communication overhead with higher energy costs.

In these simple architectures, the device application defines the practical energy consumption of the device in the end. As a result, common implementation approaches from wired devices cannot be simply transferred to WSNs. For example, if a system integrator implements an illumination sampling periodically with a 100 ms interval and transmits all messages as it is usually done for wired devices, the device battery will scarcely last for a year. Two general design principles should be used for WSN: first, allow the node to sleep as often and long as possible and second, process information locally, as processing consumes significantly less power than transmitting [14].

Adaptive sampling approaches transmit samples only if necessary and, thus, require less energy. They are generally easy to implement and decide locally for each sample, if it is transmitted. So, there is no communication or control overhead with other devices. Adaptive sampling approaches are known since the 60’s [16], but their practical value for energy efficiency is still discussed. Previous studies like [9, 10] for WSNs compared the arrival rate of single approaches to periodic sampling in open loops for simple signals, like a step response. The authors are not aware of a comparison of the approaches in a practical application scenario with a realistic energy model.

This paper analyzes different adaptive sampling approaches in two realistic scenarios defined in the next section. The simulator used for experiments is introduced in Section 3. The sampling approaches and their results are discussed in Section 4. Section 5 concludes the comparison.

2. Scenarios for comparison

The scenarios used in this paper cover various practical aspects. First, two characteristic scenarios for building automation are used, which have very diverse properties and cover a wide aspect of signals. The room temperature is generally a slow changing process. Heating and cooling usually take time, to our discomfort, and the fastest changes for the room temperature are air movements created by ventilators or air conditioners. In contrast to the temperature, the room illumination is very fast. If the light is switched on or if the sun eclipses behind a cloud, the illumination changes nearly instantly.

Both signals are evaluated in a closed control loop scenario detailed in the next section. In contrast to a monitoring scenario, sampled values need to be transmitted at once and cannot be collected over a time period to be sent energy-efficient in one message [4]. A closed control loop has further tight real-time requirements: delays, jitter and the sampling interval influence the quality of control and can cause control loop instability [7, 18].

It is not relevant in this experiment, if sensor and actuator communicate directly or via a wired base station. In both cases it is assumed, that the network has no relevant transmission delays and their influences can be neglected. Therefore, the sampling period has to be significant larger than the network delay and usually is, as seen below. Message losses, e.g., due to interferences, collision or buffer overflows, are also not considered as well as correcting message services like acknowledgements, repeats, etc. These presumptions keep the comparison independent of any technology and focus it on its topic of sampling approaches.

3. Simulation model of a single room

A realistic simulation model of a single room in Mat-lab/Simulink is used to evaluate the scenarios. The room is automated with a temperature control, a light control, electric sun blinds, and a ventilation controlling the air quality. To optimize the energy consumption of the room, the temperature and light control depend on the presence of persons. Their coming and going is simulated over the business hours. The simulation model was verified against the common simulation software TRNSYS [17].

If a person is present, the room it is either heated or cooled to 22°C, otherwise the set-point of radiators is set to 18°C and to 24°C at the cooling ceiling. To prevent that heating and cooling are activated at the same time if the temperature control oscillates due to disturbances, the modus is switched with a hysteresis of 1°C. Hence, if a person is present and the current mode is heating, the room temperature has to pass 23°C to activate the cooling.

Slow disturbances are induced by the heat exchange with the outside and with the neighboring rooms by windows and walls. Heat exchange with the outside is intensified if the ventilation is activated. Incoming sunlight and body heat of persons also influence the temperature.

Light control is set to 500 lx office illumination if a person is present, otherwise the light is off. The only disturbance is the natural sun light passing window and sun blinds. On a bright summer day the direct outdoor illumination reaches values of 120000 lx. Sun blinds are down then and block most of the direct light and only about 10% reaches the room as diffuse light in this example. Hence, artificial light is usually off on a bright summer day, while the light control has to react often on a cloudy winter day when sensor values change often. In contrast, sensor values do not change at all for long periods during night, when the light level is too low to be sensed.

This complex simulation scenario was selected, because it contains many realistic disturbances like weather, moving people, set-point changes, etc. Therefore, the simulated results of temperature and illumination sensors as well as the simulated closed control loops can be assumed as realistic, while still being manageable to perform the necessary number of experiments for a comparison.

Each simulation in the later comparison covers a full central-European year of 365 days with a fixed simulation step size of 1 s for the temperature and 100 ms for the illumination. The disturbance processes (sun light,
people, ventilation, etc.) are identical for each simulation to keep them comparable. Hence, variations in the system behaviour between simulation runs are always a result of the sampling approaches. The measured values for the temperature and illumination sensor are the number of wake-ups $N_{\text{wake}}$ and sent messages $N_{\text{msg}}$. As the sampling results in an information loss of the continuous signal, the integral absolute error of sampling $\text{IAE}_S$ is used to evaluate the quality of information at the receiver (controller). $\text{IAE}_S$ integrates the difference between continuous process value $y(t)$ and latest transmitted sample value $y_k$ in time interval $[t_L, t_U]$ assuming a zero-order hold in the receiver creating the continuous output $y_k(t)$ from the event-based signal $y_k$.

$$\text{IAE}_S(t_L, t_U) = \int_{t_L}^{t_U} |y(t) - y_k(t)| \, dt. \quad (1)$$

The control loop performance (quality-of-control) is measured by the integral absolute error of control $\text{IAE}_C$ that integrates the difference between the set-point value $w(t)$ and the continuous process value $y(t)$ via

$$\text{IAE}_C(t_L, t_U) = \int_{t_L}^{t_U} |w(t) - y(t)| \, dt. \quad (2)$$

The mean settling time $\bar{T}_S$ is the time the loop needs to reach and remain within a 5% error band of a set-point jump. The mean overshoot $\bar{O}$ is the over-response to a set-point change in percent relative to the set-point jump. Refer to Fig. 2(b) for a visualization of the criteria. The $\text{IAE}_C$ is computed in this paper only during the time the controllers are activated, i.e., if people are present in the room and, in case of the illumination, if the incoming natural light is lower than the set-point.

The energy consumption at the sensor is estimated with the energy model of a Telos rev B node presented in [4]. In this model, one wake-up for temperature sampling needs approximately 9 $\mu$A_s and for sampling the illumination 12.2 $\mu$A_s. The sending of one message costs 227 $\mu$A_s. The node requires extra $e_{\text{base}} = 283.8$ As per year in deep sleep mode LPM3 consuming 9 $\mu$A_s. The costs for higher sleep modes for sampling and transmission are included in the individual costs.

4. Results

4.1. Periodic sampling

Before the energy-efficient sampling algorithms are compared in the next subsection, a periodic sampling loop is investigated to demonstrate the basic behaviour and to establish the basis of comparison.

In case of periodic sampling, a continuous signal $y(t)$ (the room temperature or the illumination) is sampled with a constant period $T_A$. This results in a time series of samples $y_i = y(t_i)$ and time values $t_i = i \cdot T_A$, with sample index $i$. The sampled value is handled as double float value in the simulation, while quantization and measurement disturbances are ignored. As each sampled value is transmitted, the value $y_k$ at the controller equals $y_i$.
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integral absolute error of control integral error rises only slightly. Beyond 120 s, the integral error rises exponentially as the closed loop tends to instability. Fig. 5(a) shows an identical behaviour for the illumination control. The IAE_C is quite constant for a sampling period below 5 s. Above this sampling period, the IAE_C rises due to worse sampling conditions.

As a rule of thumb it can be said that the energy consumption divides to half, if the sampling period is doubled. With a sample period of 1 s, the sender requires 7446 As for wake-up, sampling and sending each sample. In contrast, sampling with 10 s requires 10% of this energy with the identical IAE_C, T_S and O. The energy falls to 62 As for a sampling period of 120 s. Therefore, the sampling period influences directly proportional the IAE_C and inversely proportional the energy consumption.

The trade-off behaviour between IAE_C and energy consumption is typical for all sampling approaches in Fig. 4 and 5. The optimal working point for the temperature seems to be at a sampling period of ca. 120 s and ca. 5 s for the illumination. The IAE_C is a good overall criterion for the quality of control, but for good reason not the only one. The mean overshoot and the mean settling time double for T_A = 120 s to 15% and 25 min in comparison to T_A = 10 s for the temperature (Tab. 1). Additionally, 17% (+11%) of the step responses do not settle at all within the evaluation window of 2.5 hour. In case of the illumination control, the mean settling time rises from 2 s to 23 s with a 45 s maximum (Tab. 2). This approves that it is not advisable to approach this critical point, but to use a sampling frequency 6 to 20 times larger than the Nyquist frequency.

4.2. Send-on-delta sampling

Send-on-delta sampling (SoD) is the most common adaptive sampling approach in building automation, often used to save network bandwidth. It has been suggested for wireless networks too [9, 10]. Basically, send-on-delta samples the signal with a fixed period T_A like periodic sampling, but transmits messages only if the sampled value y_i differs more than a given δ to the last trans-

(Fig. 1(b)). This instant behaviour makes it necessary to control the illumination with an I-controller, which successively increases the dim value until the required value of 500 lx is reached. However, a simple I-controller would be either very slow rising or windup very fast and result in a control loop instability. The quality of control can still be provided, if the I-controller is modified and only executed when new messages arrive or the set-point was changed. This results in a similar behaviour in Figures 3(a) and 3(b) with an increasing time scale only. The modifications prevent the illumination control loop from getting unstable for increased sampling periods, but the integral absolute error of control IAE_C shoots up from 121 °C s to 9100 °C s, and the settling time increases from 0.6 s to unacceptable 50 s.

The sampling period can be parameterized with the Nyquist-Shannon sampling theorem. It says that a band-limited signal with maximal frequency f needs to be sampled at least with a frequency f_s > 2f to be restored to the original signal. In control loops, it is usually necessary to work with frequencies 6 to 20 times of the system frequency f of the loop due to approximation errors that are inserted by the analog-to-digital conversion. These considerations are also valid for adaptive sampling approaches, augmented with the fact that these approaches introduce further quantization errors [7].

Fig. 4(a) shows the energy consumption of periodic sampling over its integral absolute error of control IAE_C for the simulated year of room temperature. The sampling period was increased from 1 s (upper left point) to 300 s (lower right). For a sampling period below 120 s, the integral error IAE_C rises only slightly. Beyond 120 s, the integral error rises exponentially as the closed loop tends to instability. Fig. 5(a) shows an identical behaviour for the illumination control. The IAE_C is quite constant for a sampling period below 5 s. Above this sampling period, the IAE_C rises due to worse sampling conditions.

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T_A = 0.1 s
(b) T_A = 10 s

Figure 3. Step response of the illumination on day 30 for different sampling periods T_A.
mitted value $y_k$ with $k < i$. This transmission is often limited with a min-send-time $T_{l}$ and max-send-time $T_{u}$, specifying the minimum and maximum inter-sampling intervals ($T_{l} \leq t_i - t_k \leq T_{u}$). The min-send-time prevents babbling-idiot problems if the sensor has for example a loose contact, while the max-send-time permits a heartbeat/alive check for the device. Summarizing, a message is sent if the following condition evaluates true after sampling the value $y_i$ at time $t_i$:

$$\left(||y_i - y_k|| \geq \delta \right) \land L \lor U$$

(3)

with the conditions for the min-send-time $L = (t_i - t_k \geq T_{l})$ and max-send-time $U = (t_i - t_k \geq T_{u})$ that also will be used in the next equations.

The considerations about Nyquist-Shannon sampling theorem made for periodic sampling are also valid for the send-on-delta. Additionally, send-on-delta introduces a quantization error limited by $\delta$. For large $\delta$ this significantly influences the control loop properties [7]. Further, not all samples are sent, which adds an inherent loss of information and reduces the robustness to message losses. As a result, send-on-delta may require a higher sampling period to achieve the same quality of control.

As the min-send-time $T_{l}$ defines the lower limit of the interval between messages, it has to fulfil the same condition as the sampling period in relation to the Nyquist-Shannon sampling theorem. The min-send-time is useful in the wired domain, where devices may repeatedly sample as fast as possible and can jam a network. The min-send-time loses its meaning in WSNs as the sampling period to achieve the same quality of control.

The relationships of energy consumption and $IAE_C$ for send-on-delta sampling are displayed in Fig. 4(a) and 5(a). Any experiment with a curve lower (energy) and more right ($IAE_C$) than the shown periodic sampling has a better trade-off behaviour. With a delta of 0.05°C the energy consumption falls by 95% in case of a 10 s sampling period for the temperature sampling (Table 1). For a sampling period of 120 s, 80% of the energy can be saved and for 300 s at least 52%. The Fig. 4(a) shows that an increase of the $\delta$ has no significant influence on the energy consumption, because the limitation factor is the number of wake-ups $N_{wake}$. The reason is that the temperature changes in mean only $7.89 \times 10^{-3}$°C/s with a maximum of 0.027°C/s. Hence, the delta is significant larger and saves many messages anyway. The same behaviour can be observed for the illumination in Fig. 5(a). At $\delta=1.1x$ the energy consumption is reduced to 90% with a sampling period of 0.5 s and to 60 % for $T_{\lambda} = 20 s$.

It is also visible that the $\delta$ has significant influence on the integral absolute error $IAE_S$. The first reason is the quantization error imposed by $\delta$. This leads to approximation errors in the integral and derivative parts of the controller. Another reason are limit cycles, i.e., oscillation of the process value around the set-point with amplitude $\delta$. Limit cycles are typical for all adaptive sampling approaches presented in this paper due to accuracy limitations laid on by the deadband, which presents a sort of non-linearity [11]. Usually the max-send-time is not small enough to prevent limit cycles. Control approaches like [19] can eliminate them partly, but require a special PID implementation. Limit cycles increase the number of messages and reduce the battery lifetime.

4.3. Integral sampling

Integral sampling sends a message, if the estimated integral sampling error $IAE_S$ since the last message is larger than a limit $\delta_t$. This bounds the $IAE_S$ in contrast to send-on-delta sampling and permits a slow settling to the setpoint in the control cycle [8]. A min- and max-send-time can be applied as well, leading to the condition

$$\left(\sum_{j=k+1}^{i} ||y_j - y_k|| \cdot T_{\lambda} \geq \delta_1 \right) \land L \lor U$$

(4)

Integral sampling has the same requirements laid by the Nyquist-Shannon sampling theorem as the send-on-delta sampling. The quantization error is not directly related to $\delta_t$ as in send-on-delta sampling but cannot be neglected either.

To simplify the comparison of integral and send-on-delta sampling the parameters $\delta_t$ and $\delta$ are related. Assuming, the value changes exactly by $\delta$ in one time step $T_{\lambda}$, then integral sampling creates a message as well, if the estimated error $IAE_S \approx \delta \cdot T_{\lambda}/2$ equals $\delta_t$. Hence,

$$\delta_t = \delta \cdot T_{\lambda}/2.$$ 

Fig. 4(b) and 5(b) display the energy-$IAE_C$-relationship of integral sampling. The $IAE_C$ depends significantly less on delta, since $IAE_S$ is more strongly limited, but small disturbances quickly add up and trigger more messages (Table 1, 2). The $IAE_S$ can also be limited in send-on-delta sampling by using the max-send-time $T_{U}$.

4.4. Gradient-based integral sampling

The limiting factor in the energy consumption for the send-on-delta and integral sampling are the wake-ups. To assure a good quality of control even in worst cases, the underlying sampling period needs to be small. But, each wake-up costs the energy for sampling and accumulates for the illumination with the sampling period 0.1 s already to 3855 As and for temperature with 1 s to 285 As. To reduce the energy consumption further, the number of wake-ups needs to be lowered without reducing the quality of control.

Gradient-based integral sampling [12] adjusts the sampling period $T_{\lambda}$ for each period. The idea is to use the
Figure 4. IAEC for the temperature control.

Table 1. Comparison of the results for the temperature ([\(T_s\]=s; [\(\delta\]=°C; [\(\delta_t\]=°C s; [\(N_s\)= N; [\(IAE_s\)= °C s; [\(O\)=%; [\(e_s\)= AS]).

Now, the sampling period \(T_{A,i+1}\) should be chosen so that \(1/S\) of the limit \(\delta_t\) is reached, i.e., the equation \(IAE_{S,i+1} = \delta_t/S\) is met. Solving the equation leads to

\[
T_{A,i+1}^* \approx \frac{|y_i - y_k|}{2m_i} + \sqrt{\frac{|y_i - y_k|^2}{4m_i^2} + \frac{2\delta_t}{m_i S} - 2IAE_{S,i}}. \tag{8}
\]

Different cases can occur on device wake-up after the estimated sampling interval. In the best case, the signal changed as estimated and the \(IAE_S\) approached \(\delta_t\) within a tolerance percentage \(\varepsilon\). If the signal changed less than expected, the device can estimate a new sampling interval and enter sleep mode again. A modified version of condition (4) is evaluated at each wake-up therefore

\[
((IAE_{S,i} \geq (1 - \varepsilon)\delta_t) \land L) \lor U. \tag{9}
\]

To avoid the triggering of samples by small disturbances, a low-pass filter can be necessary to smooth the gradient.
The device tries to wake-up one time within the sampling interval. The step factor $S$ specifies the number of intermediate wake-ups. It is computed in each step from the maximum factor $S_x$ relative to the percentage of $IAE_S$ within $\delta_1$ to

$$S = \min\left( S_x, \max\left( 1, \left[ 1 - \frac{IAE_S}{\delta_1} \right] (S_x + 1) \right) \right). \tag{10}$$

For example, with a maximum stepping factor $S_x = 2$, the device tries to wake-up one time within the sampling interval. If the $IAE_S$ reaches 48% of $\delta_1$ in the interval between samples, the stepping factor $S$ is computed to 1, meaning that the next sampling interval is estimated directly and not bisected again.

The illumination may be assumed as the worst-case scenario for gradient-based sampling. On the one hand, it stays dark during night (the gradient is small). Equation (8) computes then to an infinite sampling period and results in a deadlock of the device. On the other hand, the illumination may change its value during day time very quickly due to disturbances or set-point changes. Such jumps need to be detected quickly to track the set-point timely, but the maximum detection delay is unlimited. Both problems can be addressed by a max-send-time that wakes the device up after $T_U$ and transmits a message even without change of the value. To eliminate these messages, a mandatorily max-sleep-time $T_W$ is introduced analogously to $T_U$, which wakes up the device, but sends a message only after condition (9) is evaluated true. A min-send-time is useful for gradient-based sampling to define a minimum sampling interval. The limited sampling period is finally estimated by

$$T_{A,i+1} = \min(T_W, \max(T_L, T_{A,i+1})). \tag{11}$$

The mandatory limitation of the sampling interval to a maximum $T_W$ defines a wake-up period again. Hence, if regular wake-ups cannot be avoided, what is the benefit to integral sampling?

The benefit hides in the device parameterization. In the last section, the limitations laid by the Nyquist-Sampling theorem were discussed. The main problem of these approaches is the limitation of the minimum sampling frequency by the sampling interval $T_A$, which should always be hold. In contrast, the gradient-based has no minimum sampling period except for the min-send-time. Hence, it is possible to set $T_W$ larger than in send-on-delta and in integral sampling.

Basically, gradient-based integral sampling has the same reduced dependence on the delta as integral sampling in Fig. 4(c). However, the $IAE_C$ is even lower.
than for periodic sampling, especially for large max-sleep-times $T_W$ and small deltas $\delta$. Also the mean overshoot $\bar{O}$ is reduced from 15% to 10% for a sampling period $T_A$ resp. a max-sleep-time $T_W$ of 120s and also halved for 300s. The energy consumption of gradient-based sampling in Table 1 is higher for the same $T_W = T_A$ than for integral sampling. Not surprising, as the device reduced the sampling interval where necessary. However, the energy saving results from the fact that a higher $T_W$ is possible. With $T_W = 120s$, the device requires only 20% of the energy for an integral sampling with $T_A = 10s$ and 1% of periodic sampling, but the maximal reaction latency also increases up to 120s/$S_C$.

The illumination control was mentioned earlier as the worst case for the gradient-based sampling and, indeed, the results in Fig. 5(c) as well as Table 2 show less explicit advantage. Still, the settling time $T_S$ and the $IAE_C$ are lower for $T_W = T_A = 5$ and 20s and the energy consumption of gradient-based sampling at $T_W = 5s$ is only 25% of the energy consumption for integral and 3.5% of periodic sampling at $T_A = 0.5s$.

5. Conclusion

All result figures showed that the quality of control (in terms of the $IAE_C$) and the energy create always a trade-off. The trade-off curves of adaptive sampling approaches depend strongly on the selected delta $\delta$ and sampling period $T_A$. It was discussed that the sampling frequency in case of adaptive sampling approaches should be set 6 to 20 times larger than the Nyquist frequency to achieve high quality-of-control. Adaptive sampling approaches save a lot of energy in that case. Integral sampling provides the better control loop performance at large sampling periods and in absence of small stochastic disturbances. Send-on-delta has a lower energy-consumption and should be used if the quantization error is less relevant, e.g., in monitoring or non-critical control applications. Both approaches are easy to implement and provide fast reaction times limited by $T_A$. If the reaction latency is less relevant, gradient-based sampling can save most energy, especially if the energy-consumption of wake-ups and sampling actions is high.

For reasons of representativeness, a simple zero-order hold and common PID algorithms were used. First tests with model-based and heuristic-based control algorithms adjusted to adaptive sampling [19] show a substantial improvement of the quality of control for all adaptive sampling approaches with comparable results.

References


