Trade-Off Between Measurement Accuracy and Quantization Precision for Minimum Bayes Risk in Wireless Networked Control Systems

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***Abstract*—In this work, we focus on the transmission of measurements to an estimator over a wireless communication channel with limited capacity. The process it divided into two phases, measurement and transmission. In the first phase, multiple noisy measurements of the sensor value, which is assumed to stay constant over those measurements, are taken. More measurements can improve the accuracy, but also consume more time and energy. These measurements are aggregated into a sum value, which is quantized and transmitted over the communication channel with limited capacity. The measurement and transmission phases share the same time and energy budget, which limits the number of measurements and the number of bits that can be transmitted.At the receiver, the aggregated value is fed into an estimator optimized for a certain Bayes risk distortion function. Since the resources used for measurement and transmission are limited, a trade-off between measurement accuracy and quantization precision for minimum Bayes risk is found. Moreover, the influence of different resource limits for time and energy, as well as different ratios of the resources used by the measuring process and the transmission process are investigated. Both parameters show great influence on the optimum time and energy resource allocation.**

***Index Terms*—Wireless Networked Control Systems, Measurement Accuracy, Quantization Precision, Bayes Risk, Internet of Things, Communication and Control**

I. Introduction

Nowadays, the Internet of Things (IoT) receives growing attention from many different research fields, e.g. industrial communication [1] or connected cars [2]. The enormous amount of additional smart devices deployed will greatly increase the number of devices per area [3]. Many devices will act as autonomous agents and not only do sensing, but also cooperate to fulfill tasks [4]. Most of them will use a wireless connection for communication, which results in increasing competition for the available communication resources like frequency bands. The sensors will be used for sensing many different types of values like temperature, humidity, air pressure, filling levels of tanks, positions, or velocities.

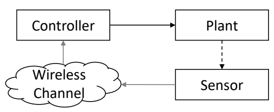

Fig. 1. The general wireless networked control loop

The sensors will often be part of control loops as shown in Fig. 1. The control loop contains the sensor, which senses the current state of a plant. The sensor values are then transmitted over a wireless communication link to a controller, which generates a control value to control the plant, which is either connected to the controller by wire or also uses a wireless connection to receive control values. The two phases of sensing and transmitting often compete for available resources at the sensor, e.g. time or energy for measuring values and subsequently transmitting them. Networked Control System (NCS) are often used in multi-agent systems, where the sensors will generate a huge amount of data, which is not used directly at or close to the sensor, thus needing communication. This work focuses on this transmission of sensor values between sensor and controller.

One example for such control systems is smart logistics [5], where many small vehicles act as the plants and distribute products. During operation, a huge amount of data, e.g. position, remaining fuel, or battery power, is collected by sensors on the vehicles and is then used at central controllers to calculate individual control actions for the devices, for example to schedule refueling of vehicles. Since the devices are moving most of the time, a wireless connection is required.

Another example are cognitive buildings, which have numerous sensors installed in all areas [6]. Here, environmental data, like temperature, humidity, or air pressure is collected as well as the presence of humans is detected. From the collected data, the overall system behavior including the user preferences can be learned by a central controller. This controller then drives plants like blinds, lightning or heating. Even in this static application with fixed sensors, a wireless connection simplifies the installation, especially in existing buildings.

From those examples, it can be clearly seen that the sensors and corresponding controllers are often separated and a wired communication link is not desired for different reasons. In this case, the communication has to be wireless, and the increasing density of devices increases the competition for the limited wireless communication resources. Additionally, the devices often rely on battery power, which imposes additional constraints on the energy consumption of the systems. The examples show two main classes of NCSs. Firstly, there is the class of decentralized NCSs, where independent sensors and agents compete for transmission resources. Secondly, there are centralized NCS, which rely on a central entity, which coordinates all agents and also the transmission resources.

Such a central scenario is considered in [7], where a central entity measures system states and signals them to the devices in the field. The communication is scheduled based on the system state deviation, but the control law is not adapted to the communication channel state. A decentralized model is used in [8], where autonomous agents in the field compete for limited communication resources used to transmit sensor values. In [9], a digital transmission chain is used to transmit sensor data. The objective is to find the optimum power allocation in transmitting the sensor values reliably.

A slightly different objective is considered in [10], which looks at the packet size of sensor networks and tries to find a trade-off between packet error probability and data integrity. In all these works, the data from the sensor is not interpreted and processed prior to transmission, but rather the raw values are transmitted. The acquisition is not adapted to the communication system state, and similarly, the process of measuring and then transmitting the data is not adapted to the state of the underlying control system plant. Sensor outputs with a certain resolution are not compressed for transmission by reducing the resolution, even if the control system plant state would only require a coarse control action, which can also be generated from a coarse input.

In [11], the transmission power is adapted to harvested energy, which also influences the estimation error of the sensor value at the receiver. The objective is to keep a control loop stable, despite the error introduced by the wireless transmission, while the harvested energy varies over time. The transmission uses an analog transmission scheme to be able to directly relate transmission errors to sensor data estimation errors at the receiver. However, the analog scheme complicates the processing at the receiver.

In [12], the influence of very low resolution analog-to-digital conversion is considered. A receiver with only 1-bit quantization is used for channel estimation. The estimation performance is improved by exploiting information about the temporal evolution of the channel.

In this work, we focus on a single sensor-receiver pair and use the properties of the underlying measurement model and communication model to jointly optimize the quality of the estimation at the receiver. Multiple noisy measurements of a parameter are taken and aggregated afterwards. The aggregated value is quantized and transmitted over a wireless channel. For both phases, measurement and transmission, only limited time and energy is available. The time limit results from the large amount of devices competing for transmission time. This limit can directly be translated to a limit of the data bits that can be transmitted in one time slot. On the other hand, a high transmit power to improve the signal-to-noise ratio (SNR) at the receiver might drain a prohibitively high amount of energy from the batteries of mobile or embedded devices. For this reason, a limitation in resolution of the quantization prior to the transmission is needed. As each individual measurement is also consuming time and power, the two phases of measuring and transmitting compete for the available time and energy resources. To find the best ratio of number of measurements and number of quantization intervals for a given time or energy limit, the Bayes risk is used as an estimation quality measure. This joint optimization of the number of measurements and the number of quantization steps allows for a minimum Bayes risk for given time or energy resource constraints.

II. System Structure

This work focuses on the sensor value measurement and transmission, so only the part of the control loop in Fig. 1 with the sensor, wireless channel and controller will be modeled. The detailed chain of the measuring sensor with transmitter, receiver and estimator is shown in Fig. 2. The measured quantity, denoted by w, is observed by a sensor and impaired by noise, denoted by m. A batch of N_{meas} noisy measurements of w is taken sequentially, denoted by $x_1, \ldots, x_{N_{\text{meas}}}$. Each individual measurement takes the time T_{meas} and the energy E_{meas}. The measurement values are then aggregated into a single value s, which is subsequently quantized into one of Q_{quant} data symbols, denoted by y. The symbol y is then transmitted over a wireless communication channel and distorted by receiver noise z. The number Q_{quant} of quantization steps determines the time and energy spent for transmission, denoted by T_{tx} and E_{tx}, respectively. The total energy and time for measuring and transmitting are limited by E_{max} and T_{max}, respectively. The received symbol, denoted by y', is then decoded according to a codebook. The output v of the decoder is used by the estimator Ψ to generate the estimate $\hat{w}$ of w. In the next subsections, the individual steps are described in detail.

A. Measurement Model

The value of $w \in \mathbb{R}$ is assumed to lie between w_{min} and w_{max} and follow a known probability-density function (pdf) $p_W(w)$. w is assumed to stay constant during the N_{meas} measurements, but with varying noise m. The noise is assumed to be Additive White Gaussian Noise (AWGN) with zero-mean and variance σ_{M}^2. The complete measurement phase takes the time $T_{\text{acq}} = N_{\text{meas}} T_{\text{meas}}$. Likewise, the complete energy for measuring is $E_{\text{acq}} = N_{\text{meas}} E_{\text{meas}}$. The pdf $p_W(w)$ as well as w_{min}, w_{max} and σ_{M}^2 are assumed to be known at the transmitter and the receiver, since they all are properties of the sensor and the observed process.

To generate the aggregated value s, the measurement values $x_n = w + m_n, n = 1, \ldots, N_{\text{meas}}$ are summed up, which is assumed to take no additional time or energy. Instead of the sum the mean could also be chosen, since they are related by the number of measurements and the receiver can find the same optimum trade-off between the number N_{meas} of measurements and the number Q_{quant} of quantization steps as the sensor, since the properties of the random value v, the measurement noise m and the resource limits are known to the receiver.

B. Quantization and Transmission Model

The quantization of the sum value s to the data symbol y is carried out according to a Q_{quant}-step function $\phi_{\text{Q}} : \mathbb{R} \mapsto$

$\{1, 2, \ldots, Q_{\text{quant}}\}$. From [13], it is known that the mutual information between sender and receiver over a binary symmetric channel is maximized for equally probable transmit symbols. To achieve this, ϕ_{Q} is designed to have equal probability for each step, based on the pdf $p_S(s)$ of s, which can be generated from $p_W(w)$ as shown in section III.

The resulting transmit symbol y is transmitted over a wireless communication channel. This transmission is subject to receiver noise z, which is assumed to be AWGN with zero-mean and variance σ_{Z}^2. The channel has the constant channel coefficient h and the transmit power is given by P. For a capacity $C = \log_2\left(1 + \frac{hP}{\sigma_{\text{Z}}^2}\right)$, the channel is assumed to be error-free, thus, for the received symbol, $y' = y$ applies. Since each transmit symbol is equally probable, all symbols can be encoded by the same number N_{bits} of bits. It is determined by $N_{\text{bits}} = \log_2(Q_{\text{quant}})$, which is not necessarily an integer number, if Q_{quant} is not a power of 2. To transmit a non-integer number N_{bits} of bits, the communication systems symbol alphabet has to be designed with Q_{quant} different symbols.

The time T_{bit} consumed for transmitting one bit is determined by the channel capacity C as $T_{\text{bit}} = \frac{1}{C}$. Since increased transmission power P increases the capacity C logarithmically, linearly increasing the energy E_{tx} for transmission logarithmically increases the possible number N_{bits} of bits. This results in a direct proportionality of Q_{quant} and E_{tx}, i.e. $E_{\text{tx}} = Q_{\text{quant}} E_{\text{quant}}$.

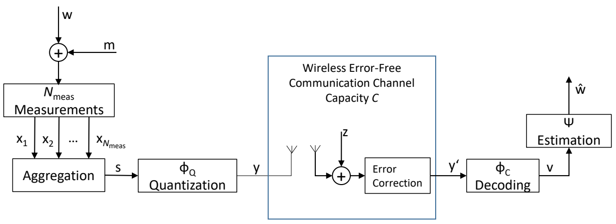

Fig. 2. System structure

C. Estimation Model

The received data symbol y' is mapped back to a value v, according to a codebook ϕ_{C}. v is subsequently used by the estimator Ψ to generate the estimate $\hat{w}$ of w. The optimization objective is to minimize the Bayes risk of the estimation, which is a metric for the estimation accuracy [14]. It is calculated according to a distortion function l, i.e. $R_{\text{B}} = \text{E}\{l\left(W; \Psi(V)\right)\}$. In this work, l is chosen to take the form $l(w, \Psi(v)) = |w - \Psi(v)|^q$ with $q \geq 1$, i.e.

$$R_{\text{B}} = \text{E}\{|w - \Psi(v)|^q\}. \tag{1}$$

For the well-known mimimum mean-square error (MMSE) estimator, $q = 2$ applies. The MMSE estimation minimizes the squared error, which is suitable, if the cost increases quadratically with the measured quantity, e.g. for an error in a voltage measurement, which results in increased power consumption. In other cases, where there is a linear dependency of the cost on the estimation error, the minimum absolute-value error (MAVE) estimator is used. An application example would be a distance measurement of drones, where the error in distance linearly increases with the time to reach a certain point with constant velocity.

D. Constraint Model

The estimation process is constrained by limited time or energy resources, which are shared between the measuring and the transmission phase. The sum time or sum energy taken by the measurement of w and the transmission of y must not exceed a certain limit, T_{max} or E_{max}, respectively. In the time limited case, the number N_{meas} of measurements determines T_{acq}, the number N_{bits} of bits determines T_{tx}. Since the transmission of the aggregated value s cannot start till all measurements have been taken, the total time spent for measuring and transmitting is sum of these times. It must not exceed the available time, i.e. $T_{\text{max}} \geq T_{\text{tx}} + T_{\text{meas}}$.

Likewise, in the energy limited case, the total energy is the sum of the energy E_{acq} consumed for measuring, determined by N_{meas}, and the energy E_{tx}, determined by Q_{quant}. The energy is constraint is then $E_{\text{max}} \geq E_{\text{acq}} + E_{\text{tx}}$.

III. Mathematical Derivations

The estimation of the sensor value w at the receiver is based on a Bayes estimation scheme. First, the probability distributions for the non-quantized case are derived. Based on these distributions, the estimators for the MMSE and MAVE case are calculated. Then, the quantization and codebook-based reconstruction is introduced. Finally, the Bayes risk, which includes the influence of the quantization, is calculated.

A. Probability distribution $p_S(s)$

In this section the pdf $p_S(s)$ is derived. The pdf of the parameter w of interest is $p_W(w)$, which is only non-zero for $w_{\text{min}} \leq w \leq w_{\text{max}}$. Each measurement is impaired with the measurement noise m, which is i.i.d. Gaussian distributed, i.e. $p_M(m) = \frac{1}{\sqrt{2\pi\sigma_{\text{M}}^2}} \exp\left(-\frac{m^2}{2\sigma_{\text{M}}^2}\right)$. N_{meas} measurement values are taken, which results in the vector

$$\boldsymbol{x} = w \cdot \mathbf{1}_{N_{\text{meas}}} + (m_1, m_2, \ldots, m_{N_{\text{meas}}})^{\text{T}} \tag{2}$$

of measurement values, where $\mathbf{1}_L$ is the all-ones vector with L elements. The sum of i.i.d. Gaussian random variables is again Gaussian, which results in

$$\sum_{n=1}^{N_{\text{meas}}} x_n = s \tag{3}$$

$$p_{S|W}(s|w) = \frac{1}{\sqrt{2\pi\sigma_{\text{M}}^2}} \exp\left(\frac{(s - N_{\text{meas}} \cdot w)^2}{2\sigma_{\text{M}}^2}\right). \tag{4}$$

This leads to the joint probability of w and w:

$$p_{S,W}(s, w) = p_{S|W}(s|w) \cdot p_W(w) \tag{5}$$

To get the unconditional pdf of s, the marginal probability w.r.t. w is calculated as

$$p_S(s) = \int_{w_{\text{min}}}^{w_{\text{max}}} p_{S,W}(s, w) \text{d}w. \tag{6}$$

B. Estimators

The MAVE estimate is defined in [14] as the upper or lower bound, respectively, which splits the integral over the a-posteriori pdf into two equal parts, i.e.

$$\int_{-\infty}^{\Psi_{\text{MAVE}}(s)} p_{S|W}(s|w)\mathrm{d}w = \int_{\Psi_{\text{MAVE}}(s)}^{\infty} p_{S|W}(s|w)\mathrm{d}w = 0.5, \tag{7}$$

The MMSE estimator $\Psi_{\text{MMSE}}(s)$ is defined as

$$\Psi_{\text{MMSE}}(s) = \int_{w_{\text{min}}}^{w_{\text{max}}} w p_{S|W}(s|w)\mathrm{d}w, \tag{8}$$

which is the expected value of the a-posteriori pdf $p_{S|W}$.

C. Quantizer design

From information theory, it is known that the optimum communication channel usage is achieved, if the mutual information between the transmitted and received values is maximized. For finite symbol alphabets, a uniform distribution of the symbols maximizes the mutual information [13]. To achieve this uniform distribution for the quantizer outputs, the quantization intervals are designed according to $p_S(s)$. In a first step, the cumulative distribution function (cdf) of S is calculated as

$$P_S(s) = \int_{-\infty}^{s} p_S(s')\mathrm{d}s'. \tag{9}$$

Then, the quantization interval bounds are calculated, with $-\infty$ as left bound of the first interval and with $+\infty$ as right bound of the last interval. The bounds p_n in between are calculated by solving the equation $\frac{n}{Q_{\text{quant}}} = P_S(p_n)$, which provides equally probable output symbols.

D. Reconstruction codebook design

Since the transmission errors from the noisy channel are assumed to be completely removed by the error correction, the received symbol y' is equal to the transmitted symbol y. At the receiver, the received symbol Y' is used to look up an input value c_n to the estimators from a codebook. The codebook is designed based on $p_S(s)$ inside the quantization intervals, i.e. the expected value for each individual interval is calculated as

$$c_n = Q_{\text{quant}} \int_{q_{y'}}^{q_{y'+1}} p_S(s)\mathrm{d}s. \tag{10}$$

E. Calculation of the Bayes risk

From (1), the Bayes risk of the MAVE estimator is given by

$$R_{\text{B, MAVE}} = \int_{-\infty}^{+\infty} \int_{w_{\text{min}}}^{w_{\text{max}}} |\Psi_{\text{MAVE}}(s) - w| \, p_{V,W}(s,w)\mathrm{d}w\mathrm{d}s, \tag{11}$$

and similarly for the MMSE estimator by

$$R_{\text{B, MMSE}} = \int_{-\infty}^{+\infty} \int_{w_{\text{min}}}^{w_{\text{max}}} (\Psi_{\text{MMSE}}(s) - w)^2 \, p_{V,W}(s,w)\mathrm{d}w\mathrm{d}s. \tag{12}$$

F. Resource Constraints

The time and energy constraints, see section II-D, limit the number of measurements as well as the number of bits which can be transmitted over the wireless channel in a given time or with a given amount of energy, respectively. The capacity limit is given by Shannon as

$$C = B \cdot \log_2\left(1 + \frac{P}{\sigma_{\text{Z}}^2}\right) \tag{13}$$

with the received signal power P, the used bandwidth B and the noise power σ_{Z}^2. For the transmission, a linear relation between the transmitted and received power is assumed. In the energy limited case, this leads to a linear relation between the available quantization steps in a given time interval T_{tx} and the transmission energy, as $Q_{\text{quant}} = 2^{N_{\text{bits}}}$ and $N_{\text{bits}} = T_{\text{tx}}C$. For this reason, a parameter γ_{E} is introduced to characterize the relation between the transmission energy E_{quant} needed for transmission of one additional quantization step and the energy E_{meas} consumed for each measurement, i.e.

$$E_{\text{quant}} = \gamma_{\text{E}} E_{\text{meas}}. \tag{14}$$

For the time limited case, the time needed to transmit one bit and the time needed to take one measurement are related by a linear coefficient γ_{T}, i.e.

$$T_{\text{bit}} = \gamma_{\text{T}} T_{\text{meas}}. \tag{15}$$

IV. Results

A. Setup

All calculations are carried out with fixed measurement noise $\sigma_{\text{M}}^2 = 9$. The range of w is set to $w_{\text{min}} = 0$ and $w_{\text{max}} = 100$. The a-priori pdf of w is set to

$$p_W(w) = \begin{cases} \frac{2w}{w_{\text{max}}^2 - w_{\text{min}}^2} & \text{if } 0 \le w \le w_{\text{max}} \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

B. Bayes risk

To get a general overview of the influence of N_{meas} and N_{bits} on the Bayes risk, the Bayes risk is calculated for up to $N_{\text{meas}} = 9$ and $N_{\text{bits}} = 9$ with both estimators, MMSE and MAVE. Fig. 3 shows $R_{\text{B, MAVE}}$ curves for different values of N_{meas} for the MAVE estimator. The more measurements are taken and the higher the quantization resolution is, the lower is the Bayes risk $R_{\text{B, MAVE}}$. For an increasing N_{meas} and a fixed N_{bits}, $R_{\text{B, MAVE}}$ decreases asymptotically, so that for a higher N_{meas} the improvement on $R_{\text{B, MAVE}}$ decreases. This is also true for increasing N_{bits} with fixed N_{meas}. For the MMSE estimator in Fig. 4, a similar behavior is observed. Please note that $R_{\text{B, MMSE}}$ is quadratic, since the MMSE estimator is optimal for the squared error. More measurements lead to a stronger reduction of $R_{\text{B, MMSE}}$ than for the MAVE estimator. Fig. 5 shows the Bayes risk for a given maximum time of $T_{\text{max}} = 13$ and $\gamma_{\text{T}} = 0.25$. The available time is completely used, i.e. $T_{\text{acq}} + T_{\text{tx}} = T_{\text{max}}$, so increasing T_{tx} decreases T_{acq} and vice versa. The results show the trade-off between T_{acq} and T_{tx} with minimum R_{B} can be found. A similar relation can be found for limited energy.

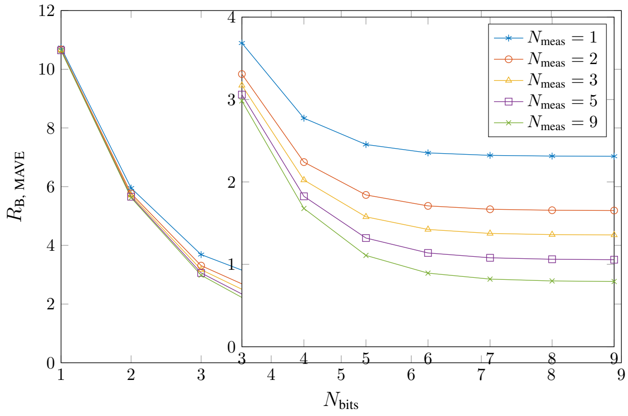

Fig. 3. Bayes risk for the MAVE estimator

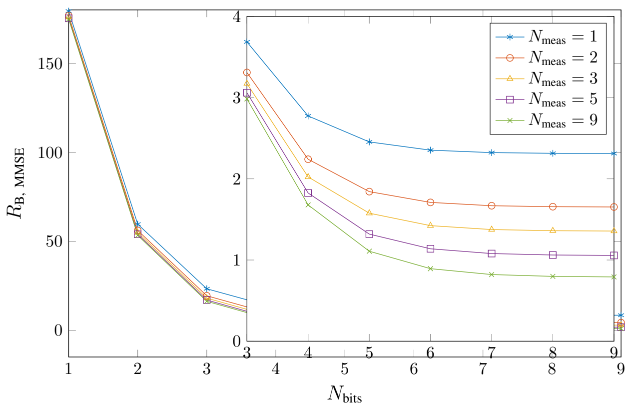

Fig. 4. Bayes risk for the MMSE estimator

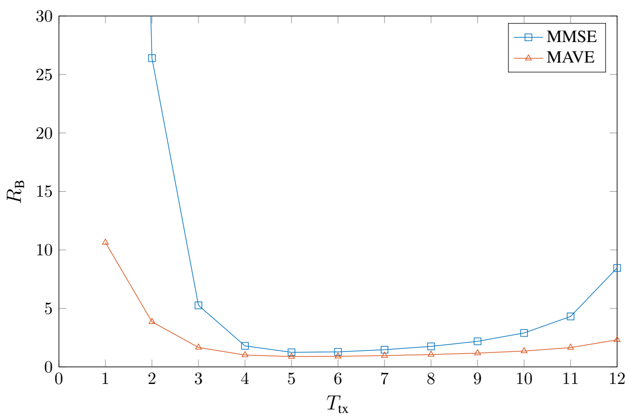

Fig. 5. Trade-off T_{tx} vs. T_{acq} with $T_{max} = 13$ and $\gamma_T = 0.25$

C. Optimum ratio of number of measurements and quantization steps

To investigate the influence of time constraints on the optimal selection of N_{meas} and N_{bits} or, likewise, energy constraints on N_{meas} and Q_{quant}, the minimum $R_{B, MMSE}$ and $R_{B, MAVE}$ for different constraint sets is investigated. First, the influence of changing constraints T_{max} and E_{max} is considered. For a fixed ratio γ_T and γ_E, respectively, the optimum allocation of time or energy, respectively, was found. From the previous results for the Bayes risk, it is clearly visible that a finer quantization and more measurements will always lead to a lower Bayes risk. This result suggests that the optimum resource allocation should always use all available time or energy resources. To find the optimum allocation for a given limit, all possible combinations of N_{bits} and N_{meas} which fully use T_{max} in the time limited case, and all possible combinations of Q_{quant} and N_{meas} which fully use E_{max} in the energy limited case, are considered. The resulting optimal values for T_{tx} and T_{acq} are shown in Fig. 6 and for E_{tx} and E_{acq} in Fig. 7. In both cases, for $T_{max} = 1$ or $E_{max} = 1$, it is only possible to carry out one measurement, but not to transmit, so the estimate is based solely on $p_W(w)$. For the time constrained case, $\gamma_T = 2$ and $T_{max} = 1$ results in only 0.5 bits available to quantize the value, so only a single value can be transmitted and the estimation is again carried out solely based on the knowledge of $p_W(w)$. Both, in the time limited and in the energy limited case, the time or energy spent for measuring, T_{acq} or E_{acq}, and transmitting, T_{tx} or E_{tx}, increase. In the time limited case, the time spent for transmission increases faster with increasing T_{max}, because one additional bit always doubles the number of available quantization steps, while the corresponding two additional measurements, which could be done in the same time, give less and less improvement for higher T_{max}.
In the energy limited case, the growth is almost proportional, because now there is just a linear instead of an exponential relation between E_{quant} and Q_{quant}. Since the improvement for each additional quantization step and measurement reduces, they increase alternating. The two estimators only show minor differences in the optimal resource allocation.

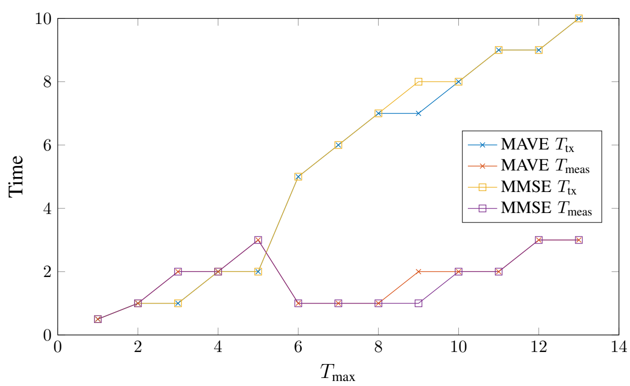

Fig. 6. Constrained time usage, $\gamma_T = 2$

Now, the influence of changing ratio γ_T is investigated. The available time is set to $T_{max} = 13$, the ratio γ_T is varied between 0.75 and 4. For rising γ_T, this makes the transmission relatively more time consuming. The results are shown in Fig. 8. The longer time per bit results in more time spent for transmitting data than measuring. This leads to a growing T_{tx}. As shown in the previous results, the overall R_B increases, since the duration of a single measurement and the available time T_{max} is held constant, while less bits can be transmitted.

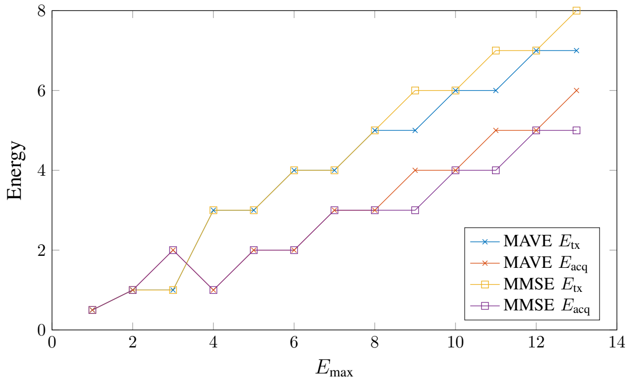

Fig. 7. Constrained time usage, $\gamma_{\text{E}} = 0.25$

Decreasing N_{bits} and increasing N_{meas} is generally not an option, because decreasing N_{bits} by one halves Q_{quant}.
For the energy constrained case, a similar result is shown in Fig. 9. Here, the linear relation between Q_{quant} and N_{meas} results in a more constant ratio of E_{tx} and E_{acq}, because, in contrast to the previous case, an additional measurement can often compensate for a smaller Q_{quant}.

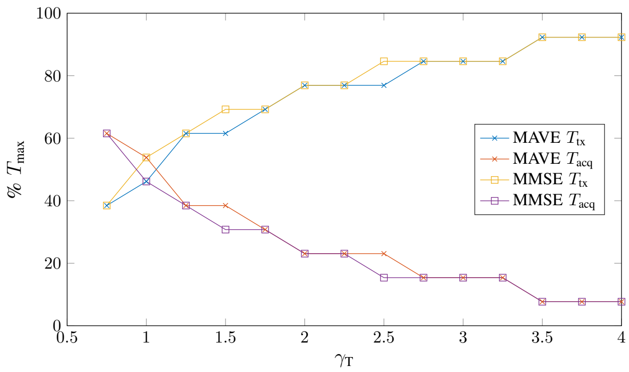

Fig. 8. Variable time usage ratio, $T_{\max} = 13$

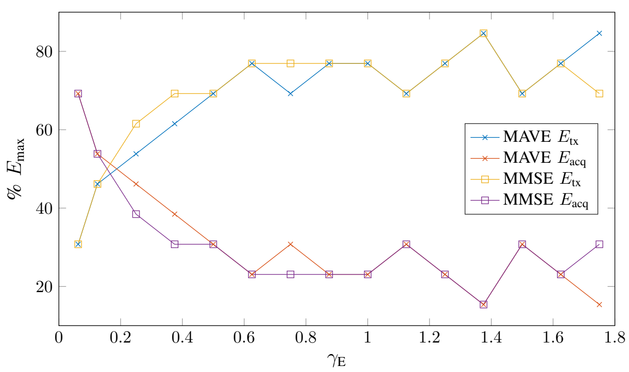

Fig. 9. Variable energy usage ratio, $E_{\max} = 13$

V. Conclusion

In this work, the estimation of a parameter following a given pdf using quantized measurements transmitted over a wireless channel was considered. Multiple noisy measurements of a parameter can be taken sequentially and are aggregated afterwards. The aggregated value is quantized and transmitted to the receiver, which executes the estimation of the measured parameter. The number of measurements in the measurement phase and the number of quantization steps is limited by a shared time or energy budget. It was shown that a trade-off between the two parameters exist. Furthermore, the different influence of time and energy limits was shown, as well as the behavior for changing ratios of the resources needed for measurement and transmission.

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