On the Transmission-Computation-Energy Tradeoff in Wireless and Fixed Networks

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Abstract—In this paper, a framework for the analysis of the transmission-computation-energy tradeoff in wireless and fixed networks is introduced. The analysis of this tradeoff considers both the transmission energy as well as the energy consumed at the receiver to process the received signal. While previous work considers linear decoder complexity, which is only achieved by uncoded transmission, this paper claims that the average processing (or computation) energy per symbol depends exponentially on the information rate of the source message. The introduced framework is parametrized in a way that it reflects properties of fixed and wireless networks alike.

The analysis of this paper shows that exponential complexity and therefore stronger codes are preferable at low data rates while linear complexity and therefore uncoded transmission becomes preferable at high data rates. The more the computation energy is emphasized (such as in fixed networks), the less hops are optimal and the lower is the benefit of multi-hopping. On the other hand, the higher the information rate of the single-hop network, the higher the benefits of multi-hopping. Both conclusions are underlined by analytical results.

Index Terms—Computation energy, transmission energy, computation-transmission-energy tradeoff, multi-hop networks

I. INTRODUCTION

A. Energy-Efficiency in Multi-Hop Networks

Recently WWRF Chair M.A. Uusitalo announced his vision of the future wireless worl1. One of his major technological visions is that until the year 2017 7 trillion wireless devices will be used by 7 billion users. Mobile communication engineers face a multitude of challenges to integrate this tremendous number of nodes such as more demanding requirements on the radio resource management, packet routing, and energy efficiency. The latter is in the focus of this paper, which analyzes the interplay of the energy consumption of the transceiver path (transmission energy) and the data processing unit (computation energy). We introduce a framework and draw conclusions, which can be equally applied to fixed networks, cellular networks, and low-complexity sensor networks.

There exists a comprehensive literature analyzing the transmission energy consumption in a wireless network such as the seminal work in [1], where a bursty protocol has been introduced. A bursty protocol shortens the online time of a node, concentrates the transmitted energy on a shorter time interval, and increases the signal-to-noise ratio (SNR) in analog multi-hop networks. Intuitively, a bursty transmission reduces the constant energy as the online-time of the node is reduced. On the other hand, the information rate is increased, which implies that the data processing unit potentially requires more energy, if the required average computation power per symbol scales super-linearly. This inherent tradeoff is not only of importance for energy-limited terminals, which have only a limited energy budget, but it is of equal importance for fixed networks where data aggregation and bursty transmission are valid alternatives to reduce the energy consumption. Due to the tremendous number of sensor nodes and the requirement for a power source such as a battery, even small energy savings per node imply a significant ‘green potential’. This inherent tradeoff of transmission and computation energy is in the focus of this work and we explore how an appropriate choice of the packet length and number of nodes in a network can reduce the overall energy consumption.

B. Related Work

In previous work such as [2], [3] the computation energy of a network has been only considered under the assumption of a linear dependence of rate and energy. In [2], the authors investigate the lifetime of a network where individual nodes collect and deliver data. In particular, it considers the transmission energy, the source behavior, network size, and also how much computation energy is required to receive a bit, which relates linearly to the information rate. Similarly, [3] also analyzed the network lifetime and applied a linear model for the computation energy. As we discuss later, a linear model does not suitably reflect the case of coded transmission, since we rather face an exponential dependency. The routing problem in wireless networks with per-bit processing-power has been analyzed in [4], where again the processing energy depends linearly on the information rate.

C. Contribution and Outline

This work introduces a framework to analyze and to assess the tradeoff of computation and transmission energy in multi-hop networks such as relay-based cellular networks, sensor networks, but also fixed networks with intermediate gateways and routers. We discuss the interplay of both and show how
packet length, data rate, network size, and the functional
description of the computation complexity affects this relation-
ship and depict potentials for the optimization of a network’s
energy consumption. The underlying system model will be
introduced in Section II. Based on this model we derive the
normalized computation and transmission energy of a decode-
and-forward (also called store-and-forward) based multi-hop
network in Section III. The tradeoff of both is illustrated in
Section IV and the paper is concluded in Section V.

II. SYSTEM MODEL

Before we present the transmission-computation-energy
tradeoff in Section III, we successively introduce our channel
model, resource model, and energy model.

A. Channel Model

We consider a network composed of the source node \( s = 0 \), the set of \( N \) intermediate nodes \( R = [1; N] \), and the
destination node \( d = N + 1 \) as illustrated in Fig. 1. This paper
focuses on an additive white Gaussian noise (AWGN) channel
with fixed channel gain. The channel input at node \( n \) is the
complex Gaussian random process \( X_n \sim \mathcal{CN}(0, P_{tx,n}) \) with
average per-symbol power \( P_{tx,n} \). Let the distance between two
nodes \( n, n' \in [0; N + 1] \) be \( d_{n,n'} \). Then the channel gain
between both nodes is \( h_{n,n'} = d_{n,n'}^{-\alpha/2} \) with path loss exponent
\( \alpha \). For the sake of notational simplification we assume in this
paper that all nodes are distributed at equal distance between
\( s \) and \( d \) such that

\[
d_{n,n'} = \frac{|n' - n|}{N + 1}d_{s,d}.
\]

This assumption is rarely fulfilled in wireless sensor networks,
but is of particular relevance in fixed networks. In addition,
the conclusions drawn in this paper do not depend on this
assumption but rather on the non-linear nature of path loss
as well as the different complexity. In the AWGN model, the
channel output at node \( n' \) is given by

\[
Y_{n'} = \sum_{n \in [0; N+1] \setminus n'} h_{n',n}X_n + Z_{n'},
\]

where \( Z_{n'} \sim \mathcal{CN}(0, \sigma^2) \) is the AWGN with \( \sigma^2 = 1 \) throughout
this paper.

We consider in this work a network of full-duplex terminals
in order to introduce the computation-transmission-energy
tradeoff. Full-duplex is easily implemented in fixed networks
where both links are physically separated using different
physical cables. However, wireless applications imply a half-
duplex constraint on the deployed nodes and therefore an
inherent rate-loss, which renders multi-hop transmission less
beneficial.

B. Resource Model and Means of Normalization

Our analysis compares the multi-hop setup with a single-
hop reference system \( (N = 0) \) with source-destination distance \( d_{ref} = d_{s,d} = 1 \), and the reference transmission power
\( P_{tx,ref} = P_{tx,ref} \). Let us assume that the source node has a fixed
amount of data collected, which is mapped to the codeword
\( W_{ref} \) with overall \( |W_{ref}| \) bits-net-data and must be delivered
to the destination. Assume that \( T_{ref} < \infty \) exclusive resource
elements (available channel uses) are assigned to the source
node, which can correspond to time slots in an TDMA system
or exclusive bandwidth in an FDMA system. Without loss of
generality we refer in the following to \( T_{ref} \) as the number of
symbols in time. In order to reliably communicate \( W_{ref} \),
the source must transmit with an average information rate per
symbol \( R_{ref} = |W_{ref}| / T_{ref} \), i.e., with each channel access
on average \( R_{ref} \) bits must be transmitted. In the previously
described Gaussian AWGN channel model the average infor-
mation rate per symbol is described by \( R_{ref} = C(P_{tx,ref} / \sigma^2) \)
with \( C(x) = \log_2(1 + x) \). Throughout this paper, we use the
number of bits \( |W_{ref}| \) as means of normalization and require
that each protocol must reliably communicate \( W_{ref} \) using at
least \( T_{ref} \) time symbols.

This normalization offers the degree of freedom to adjust
the number of used time symbols \( T' < T_{ref} \), which implies
that a node uses only parts of the assigned resources. However,
in order to deliver the same amount of data, the rate must be
increased such that \( R' = (T_{ref} / T')R_{ref} \) as per channel access
a higher number of information bits must be communicated.
In the following part, we introduce our energy model and how
the overall transmission and computation energy depend on
the active time period \( T' \).

C. Energy Model and Bursty Transmission

From the previous introduction we can immediately state
that the transmission energy in the reference system is given
by \( E_{tx,ref} = P_{tx,ref} \cdot T_{ref} \). Under the assumption that the desti-
nation decodes the transmission also in a time interval \( T_{ref} \) (in
order to avoid an accumulation of packets), it must also decode
the data with rate \( R_{ref} \). Motivated by convolutional codes,
which can be decoded using a trellis representation [5] of the
encoder’s state space, we claim that the decoding complexity
for each time symbol is exponential in the information rate
\( R_{ref} \). This behavior is caused by the fact that also the state
space and the number of possible state transitions per channel
access in the decoder-trellis expands exponentially with the
product of constraint length and \( R_{ref} \). Previous work only
considered linear complexity, which implies an uncoded trans-
mision and an actual performance loss that can be expressed
by a constant SNR gap as introduced in [6, pp. 66]. We apply
an SNR gap between exponential and linear complexity of
5 dB [6], [7], which implies that a system with linear decoding
complexity must invest 5 dB higher transmission power in
order to achieve the same performance.

The computation power can be expressed by \( P_{c,ref} \sim c_1 c_2^{R_{ref}} \) where the constants \( c_j \) are decoder specific. For the
sake of simplicity, we consider in our work \( c_1 = c_2 = 1 \).
(we neglect the constraint length as it remains the same for all $T'$) and $c_3 = 2$ such that the computation energy for a packet of length $T_{\text{ref}}$ is given by $E_{c,\text{ref}} = T_{\text{ref}} \cdot 2^r$, which is used as reference value for our evaluation of multi-hop networks. The actual parametrization changes for different coding schemes and inherently affects the quantitative results of the transmission-computation-energy tradeoff although the qualitative conclusions are not affected.

Assume the transmission length used by node $n$ is $T' < T_{\text{ref}}$, then the transmission energy is scaled such that

$$T_{\text{ref}} C \left( \frac{P_{tx,n}}{\sigma^2} \right) = T' C \left( \frac{P_{tx,n}}{\sigma^2} \right)$$

(3)

is fulfilled. This implies that the bursty protocol with $T' < T_{\text{ref}}$ requires the transmission power

$$P'_{tx,n}(\delta_t) = T' / T_{\text{ref}} = \sigma^2 \left( 1 + \frac{P_{tx,n}}{\sigma^2} \right)^{1/\delta_t} - 1$$

(4)

in order to satisfy the constraint that the same amount of data must be communicated. In addition, also the computation energy increases as the rate $R' = C (t'_n) / T_{\text{ref}}$ implies an exponential scaling of the computation energy. Let $\Delta_t = R' - R_{\text{ref}}$, then the computation energy is given as

$$E'_{c,n} = 2^{\Delta_t} E_{c,n},$$

(5)

which deviates from algorithms with linear complexity where $E_{c,n}$ scales linearly with the ratio of $R'$ and $R_{\text{ref}}$. In the following, all derivations are presented for exponential complexity while the corresponding equations for linear complexity can be easily obtained using a linear model in $\Delta_t$.

III. NORMALIZED ENERGY IN MULTI-HOP NETWORKS

In order to capture the tradeoff between transmission and computation energy in multi-hop networks, we use the decode-and-forward protocol introduced in [8] with node-cooperation and non-coherent transmission. Given the power assignment vector $[P_{tx,0}, P_{tx,1}, \ldots, P_{tx,N}]$ the maximum achievable end-to-end rate is given by [8]

$$R \leq \min_{1 \leq n \leq N+1} C \left( \frac{1}{\sigma^2} \sum_{k=0}^{n-1} h_{n,k} P_{tx,k} \right).$$

(6)

In the following, we define the normalized transmission and computation energy of a multi-hop network compared to a single-hop transmission for a fixed number of resource elements. On this basis, we extend the framework to define the normalized energy for a flexible and optimized number of resource elements in our multi-hop network.

A. Normalized Energy for Fixed $T_{\text{ref}}$

The rate on the first hop is given by

$$R_0 = C \left( \frac{P_{tx,0}}{\sigma^2} \right)$$

(7)

with the source power given as a function of the reference power:

$$P_{tx,0} = (N + 1)^{-\alpha} P_{\text{ref}}.$$  

(8)

In order to achieve the same rate on the second hop, the transmission power of the second terminal must be chosen such that

$$h_{0,1}^2 P_{tx,0} = h_{0,1}^2 P_{tx,1} + h_{0,2}^2 P_{tx,0}$$

with $h_{n,n'} = d_{n,n'}^{-\alpha/2}$

$$P_{tx,1} = (1 - 2^{-\alpha}) P_{tx,0}. $$

(9)

(10)

This can be generalized for the transmission power of node $n$ as follows

$$h_{0,1}^2 P_{tx,0} = \sum_{k=0}^{n} h_{n+1,k}^2 P_{tx,k}$$

(11)

$$= \sum_{k=0}^{n} (n + 1 - k)^{-\alpha} h_{0,1}^2 P_{tx,k}$$

(12)

$$P_{tx,n} = P_{tx,0} - \sum_{k=0}^{n-1} (n + 1 - k)^{-\alpha} P_{tx,k}$$

(13)

$P_{tx,n}$ is strictly monotonically decreasing in $n$ as illustrated in Fig. 2. Hence, the power assignment $P_{tx,n} = P_{tx,0}$ provides an achievable but suboptimal solution for wireless networks (in case of $\alpha = 4$ the maximum difference in Fig. 2 is about 0.35 dB per node) and provides the exact solution for fixed networks where no cooperation gain can be exploited. The normalized network-wide transmission energy for packet length $T_{\text{ref}}$ is

$$E_{tx,\text{norm}}(\delta_t = 1) = \frac{T_{\text{ref}}}{T_{\text{ref}} P_{ref}} \leq \frac{(N + 1) P_{tx,0}}{P_{\text{ref}}}$$

(14)

(15)

and the normalized computation energy is given by

$$E_{c,\text{norm}}(\delta_t = 1) = \frac{T_{\text{ref}}}{T_{\text{ref}} 2^{R_{\text{ref}}}} \leq N + 1,$$

(16)

which already shows that the computation energy grows faster in $N$ than the transmission energy and therefore eventually becomes the dominant term for large $N$. 

Fig. 2. Power assignment example for 5 nodes and different path loss values
An example for $E_{\text{c,norm}}(\delta_t)$ is shown in Fig. 3 for $\alpha = 3$, $P_{tx, ref} = 1$, and $\sigma^2 = 1$, which gives $R_{\text{ref}} = 1$. Similarly, the computation energy is given by

$$E_{c,\text{norm}}(\delta_t) = \frac{\sum_{n=1}^{N+1} 2R_{\text{ref}} 2\Delta r}{2R_{\text{ref}}} = \delta_t(N + 1)^2 \Delta r = \delta_t 2 \Delta r E_{c,\text{norm}}(1).$$

The rate difference $\Delta r = R' - R_{\text{ref}}$ must be such that $R_{\text{ref}} T_{\text{ref}} = R' T'$, which implies

$$E_{c,\text{norm}}(\delta_t) = \delta_t 2 R_{\text{ref}} (1/\delta_t - 1) E_{c,\text{norm}}(1).$$

An example for the normalized computation energy is shown in Fig. 4 for the reference rate $R_{\text{ref}} = 1$. Interestingly, assume $T_{\text{ref}} = 2T'$ ($\delta_t = 0.5$) and $R_{\text{ref}} < 1$ then a bursty transmission will not consume more computation energy than the direct transmission. On the other hand, if the rate increases to $R_{\text{ref}} > 1$, the bursty transmission will increase the required computation energy.

### C. Optimal Packet Length $T'$

We can easily identify the packet length, which minimizes the computation energy in the multi-hop network (once we chose $N$) to be

$$T_{c, \text{opt}} = \arg \min_{0 < T' \leq T} E_{c,\text{norm}}(T' / T_{\text{ref}})$$

$$\frac{dE_{c,\text{norm}}(T' / T_{\text{ref}})}{dT'} = 0$$

$$T_{c, \text{opt}} = T_{\text{ref}} \min ((\ln 2) R_{\text{ref}}, 1).$$

We know from (19) that the transmission energy can only increase for $T' < T_{\text{ref}}$ such that the optimal $T'$, which minimizes the overall energy consumption, must be in the interval $[T_{c, \text{opt}}; T_{\text{ref}}]$ and depends on the ratio of $E_{\text{tx,norm}}$ and $E_{c,\text{norm}}$. However, $T_{c, \text{opt}}$ provides a good lower bound on the optimal packet length and only depends on the reference rate $R_{\text{ref}}$, which simplifies its computation.

The overall energy required by the network is given as

$$E_{\text{sum}}(R_{\text{ref}}) = E_{c,\text{norm}}(R_{\text{ref}}) \cdot E_{c,\text{ref}}(R_{\text{ref}}) + E_{\text{tx,norm}}(R_{\text{ref}}) \cdot E_{\text{tx,ref}}(R_{\text{ref}}).$$

Now let $E_{c,\text{ref}} = \eta_{\text{ref}}(R_{\text{ref}}) E_{\text{tx,ref}}$, which relates the computation and transmission energy for a single-hop system depending on the actual rate. Using (4) and (5), the function $\eta_{\text{ref}}(R_{\text{ref}})$ can be expressed depending on a system-specific reference value $\eta_{\text{ref}}(1)$ (as shown in the appendix). The overall consumed energy in the multi-hop network is now given as

$$E_{\text{sum}}(R_{\text{ref}}) = E_{c,\text{norm}} \cdot \eta_{\text{ref}}(R_{\text{ref}}) E_{\text{tx,ref}} + E_{\text{tx,norm}} E_{\text{tx,ref}},$$

where $E_{c,\text{norm}}$ and $E_{\text{tx,ref}}$ are the normalized energies for reference rate $R_{\text{ref}}$ (which are omitted here to avoid any confusion with $\delta_t$). The normalized sum-energy can be expressed by

$$E_{\text{sum,norm}}(R_{\text{ref}}) = \frac{E_{c,\text{norm}} \cdot \eta_{\text{ref}}(R_{\text{ref}}) + E_{\text{tx,norm}}}{1 + \eta_{\text{ref}}(R_{\text{ref}})}.$$
complex codes, while for high-rate transmission as in fixed
coding with higher complexity is preferable over a less
N
the other hand, for high-rate transmission the computational
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energy and higher normalized computation-energy.
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the solution for fixed networks derived in (19), which also
for wireless networks using
N
Fig. 5. Tradeoff of normalized computation and transmission energy for
N ∈ [1:30] relays and reference rates Rref. Lines show the exact solution
for wireless networks and markers show the exact solution for fixed networks
(which also serves as lower bound for wireless networks). Furthermore, α = 3
and σ² = 1.

IV. RESULTS

Based on the previously described framework, we discuss
in this section results for the transmission-computation-energy
tradeoff. We focus thereby on two particular aspects. Firstly,
we analyze the jointly achievable transmission-computation-energy
curve under a given throughput-constraint, and secondly, we discuss the optimal network size and energy savings
potential depending on the reference rate Rref.

- Strange point at 1.5 value of Rref

A. Transmission-Computation-Energy Tradeoff

Fig. 5 shows the achievable transmission-computation-energy
curve for low-rate transmission (Rref = 0.1) and high-rate transmission (Rref = 2). Lines indicate the exact solution
for wireless networks using Tc,opt in (13) while markers show the solution for fixed networks derived in (19), which also
serves as approximated solution for wireless networks. Each
marker indicates one particular setup with N relay nodes
where higher N result in lower normalized transmission-energy and higher normalized computation-energy.

The minimum normalized computation-energy is lower for the
low-rate transmission than for the high-rate transmission,
which indicates that in multi-hop networks with fixed N
the relative computation-energy savings are higher for low
rates. Consider the low-rate transmission and the slope of
the curve. In the case of linear complexity, the computational
energy doubles with every additional hop irrespective of the
packet length. Hence, the normalized computational energy
for a linearly complex algorithm has slope 1 in N and is
significantly higher than for exponential complexity. On
the other hand, for high-rate transmission the computational
energy for exponential complexity also increases linearly in
N as Tc,opt = Tref. Therefore, low-rate transmission implies
that coding with higher complexity is preferable over a less
complex codes, while for high-rate transmission as in fixed
networks less complex codes are preferable with respect to
the transmission-computation-energy tradeoff.

B. Optimization of the Overall Energy

Fig. 6 shows the normalized sum-energy according to (28)
for three different values of ηref(1) and the optimal number of
relay nodes, which minimizes the sum-energy for a particular
value of ηref(1) and Rref and Tc,opt given in (25). In Fig.
6 solid lines indicate the results for exponential complexity
and dashed lines for linear complexity relative to the same
common reference power (after application of a 5 dB SNR
gap). Markers again show the solution for fixed networks while
lines show the solution for wireless networks.

Fig. 6(a) shows the optimal N depending on ηref(1) and Rref. The higher the computation energy compared to
the transmission energy (reflected by a higher ηref(1)) the
lower the optimal N. With an increasing emphasis on the
computation energy, it becomes the dominant part of the
sum-energy, which renders a higher number of nodes less
beneficial. In addition, if the reference rate is increasing, the optimal number of nodes is also increasing in order to counteract the exponentially increasing transmission energy. The slope of this increase is higher for \( \eta_{ref}(1) = -20 \, \text{dB} \) than for \( \eta_{ref}(1) = 0 \, \text{dB} \). The latter refers to fixed networks where computation energy contributes more significantly to the sum-energy than in wireless networks. In addition, networks with linear computational complexity prefer more hops than networks with exponential complexity. Further consider the optimal \( N \) at \( R_{ref} = 1.5 \) for \( \eta_{ref}(1) = 0 \, \text{dB} \). It reaches an minimum at this point as the normalized sum-energy is greater than 1 and therefore relaying is not optimal for this case. However, this is different for linear complexity as we apply a 5 dB shift, which then renders relaying beneficial again.

Fig. 6(b) shows the minimum normalized sum-energy using \( T_{c, opt} \) in (25) and using the optimal \( N \) depicted in Fig. 6(a). The lowest value of \( E_{sum, norm} \) is obtained for \( \eta_{ref}(1) = -20 \, \text{dB} \) as the transmission energy can be significantly reduced and the computation energy does not become a dominating part with increasing \( N \). With increasing reference rates, the transmission energy in the single-hop network becomes a more dominant part of the sum-energy. Due to the significant transmission power savings in multi-hop networks, also the normalized sum-energy declines with increasing \( R_{ref} \). This implies that multi-hop transmission is more useful in scenarios with high data rates and less complex decoders and encoders. We can further see that at low rates the sum-energy is higher for linear complexity than for exponential complexity while at higher rates linear complexity is again preferable with respect to the sum-energy. By contrast, for \( \eta_{ref}(1) = -20 \, \text{dB} \) (wireless case) both linear and exponential complexity achieve similar sum-energy performance (as the transmission power is dominating).

V. CONCLUSIONS AND FUTURE CHALLENGES

This paper introduced and analyzed the tradeoff of the energy required for decoding and processing transmissions and the energy necessary to transmit a message. We derived a framework, which showed that for increasing emphasis on the computational energy (increasing \( \eta_{ref}(1) \)), multi-hop protocols are less beneficial to reduce the network-wide spent energy, while for increasing emphasis on the transmission energy (increasing reference rate \( R_{ref} \)) they become more beneficial. The comparison of linear and exponential complexity showed that more complex encoding is preferable at low data rates while low complex encoding is preferable at high rates with respect to the transmission-computation-energy tradeoff. In addition, using different weighting of the transmission and computation energy as for instance in wireless and fixed networks, we showed that a smaller number of hops in fixed networks is preferable due to the significant computation energy while in wireless networks more hops are preferable due to the dominating transmission energy.

Among the next challenges is the question for the optimal complexity-function rather than for the optimal protocol or number of hops. If a functional expression of the SNR-gap depending on the computational complexity can be found, the optimal computation complexity for both wireless and fixed networks can be determined.

APPENDIX

In section III-C we introduced the function \( \eta_{ref}(R_{ref}) \), which relates the computation and transmission energy in the single-hop reference system such that \( E_{c, ref} = \eta_{ref}(R_{ref}) E_{tx, ref} \). Assume that for reference rate \( R_{ref} = 1 \) the function is predefined as a system-specific parameter. At this rate the source must transmit on the direct link with power \( P_{tx, ref}(1) \). Assume that the rate is now given by \( R' = \delta \cdot R_{ref} \), then the transmission energy is given by \( E_{tx, ref}(1/\delta) \), where we applied \( \delta \). The computation energy is given by \( 2\Delta \cdot E_{c, ref}(1) \) as given by (5). Hence, we can derive \( \eta_{het}(R_{ref}) \) as

\[
2\Delta \cdot E_{c, ref}(1) = \eta_{het}(R_{ref}) \cdot E_{tx, ref}(1/\delta),
\]

\[
2\Delta \cdot \eta_{ref}(1) E_{tx, ref}(1) = \eta_{het}(R_{ref}) \cdot E_{tx, ref}(1/\delta),
\]

\[
\eta_{het}(R_{ref}) = \eta_{het}(1) \cdot \frac{2\Delta \cdot E_{tx, ref}(1)}{E_{tx, ref}(1/\delta)}.
\]

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