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# Optimized Multi-attribute Co-design for Maximizing Efficiency in Wireless Sensor Networks

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***Abstract*—A key task in Wireless Sensor Networks (WSNs) is to deliver specific information about a spatial phenomenon of interest. However, in WSNs the operating conditions and/or user requirements are often desired to be evolvable, whether driven by changes of the monitored parameters or WSN properties. To this end, few sensor nodes sample the phenomenon and transmit the acquired samples, typically multihop, to the application through a gateway called sink. Accurately representing the physical phenomenon and reliably, timely delivering the user required information comes at the cost of higher energy as additional messages are required. This work proposes a tunable co-design for network optimization to avoid under or over provision of information and interaction of the attributes and their effects on each other. We validate the approach viability through analytical modeling, simulations for a range of requirements.**

***Keywords*-Co-design, Sampling, Information Transport, Optimization**

## I. Introduction

In Wireless Sensor Networks (WSNs), the applications are interested in the desired information from the network. Sampling the desired information accurately and reliably and timely transporting the desired physical attribute is one of the key requirements in WSNs.

Typically, in WSN the state of the art [14] considers the sampling and information transport isolated. Sampling protocols assume that the information transport to be perfect in delivering the sampled data to the end user [5]. On the other hand, information transport considers the sampling to be perfect in providing the required information for delivery to the end user [4]. This isolation of sampling and information transport leads to negotiations with user requirements and hinders the deployed WSN by delivering either redundant information or under provision of information with unsatisfied user.

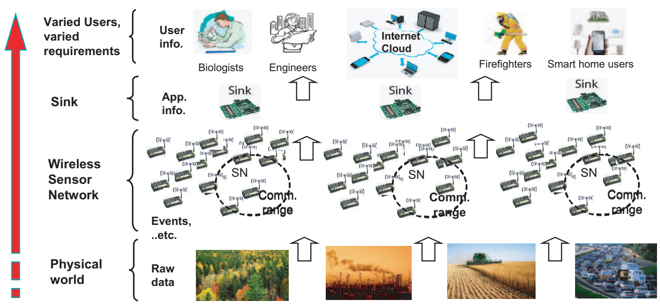


Fig. 1: Expected Integration of WSNs into IoT/sensor webs

Fig.1 shows that there are multiple users accessing information from the same WSN deployment and also from different WSN deployment for different applications. Considering the evolving requirements, the sampling and information transport should be tunable according to the application requirements.

WSNs, due to their ad-hoc nature, are subject to a wide range of operational perturbations affecting sampling and information transport. The perturbations caused by collisions, contention and congestion lead to a deviation between the attained requirements and user requirements. If the attained information requirements is higher than required, then the valuable resources are wasted in the network. Conversely, if the attained information requirement is lower than desired, the information usefulness for the application is compromised. From Fig.2, there could be various designs for WSNs, some pertaining to over provide the information (Design 2) and some under providing the information (Design 1). However, in our work we want to achieve a design such that we can provide the desired user requirements without wasting resources and satisfying the user requirements (Design 3).

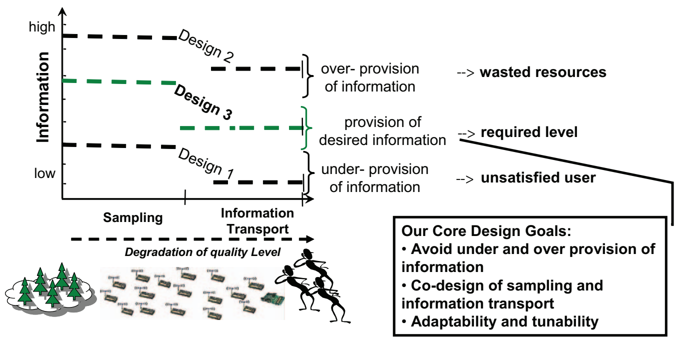


Fig. 2: On Exact Provisioning of Information in WSN

Common to all these observations is that in WSNs the operating conditions and/or user requirements are often desired to be evolvable, whether driven by changes of the monitored parameters or WSN properties of configuration, structure, communication capacities, node density, and energy among many others. In our work the challenge is in developing a design for the WSN protocol suite to avoid under or over provision of information. In addition, co-design of sampling and information transport, provide tunability for various user requirements and adapt accordingly to the user requirements.

## II. Related Work

The state of the art in WSN focus either on the sampling accuracy (e.g., [3][5][12]) or transport reliability (e.g., [1][2][4]) or transport timeliness (e.g., [8]).

In [3], the authors address the node selection for optimizing accuracy in WSN. However, the information transport is assumed to be reliable. In [5], the authors propose an efficient and adaptive approach to model sampling accuracy, reliability is implicitly assumed to be perfect. In [12], the authors address the optimized solution for accuracy, the transport reliability and timeliness are neglected.

In [1], probabilistic techniques are applied for service differentiation. However, the solution aims at providing strict conditions for messages. In [2], the authors propose multi-path forwarding to ensure end-to-end delays. However, optimizing accuracy and reliability for maximizing efficiency are missing in [1][2]. GIT [4], the proposed transport protocol yet has to be extended to consider sampling accuracy. In CFLOOD [8], the authors miss the important aspect of reliability and target maximum reliability as they focus on the detection of critical events.

In [6], we consider the tuning of transport reliability and timeliness in composition, but without addressing the sampling accuracy. In [9], the authors present a co-design of data aggregation and data transport in WSN, ignoring the sampling operation. Summarizing, to the best of our knowledge there is no prior work on sampling and transport co-design for providing application required quality with optimized tradeoffs spanning accuracy, reliability, timeliness and energy efficiency in WSNs [14]. In this work, we build first steps to fill this research gap.

## III. Preliminaries

Our system model consists of a homogeneous WSN with static SNs and one sink. We assume a default Carrier Sense Multiple Access (CSMA)-based MAC and an underlying routing protocol, which provides a path for all SN towards the sink. Each SN knows its direct neighbors, e.g., through beaconing and can communicate with each other within the hotspot.

We consider a physical phenomenon of interest that spans a specific small sub area of the WSN field. In general, the application is interested in information about this spatial phenomenon, e.g., the perimeter of its area. We consider that the sink is interested in estimating the hotspot $S$ with certain accuracy value. We consider that SN $N$ is at a certain distance with variance $\sigma_s$ due to hotspot and also with certain noise $\sigma_N$ independent and identically distributed (i.i.d.) Gaussian random variables of zero mean and variance. We also consider that any signals $Gi$ and $Gj$ between any SNs $N_i$ and $N_j$ can be with certain correlation coefficient $\rho(i,j)$ and also certain correlation $\rho(S,i)$ between hotspot source and SN $N$. Here, correlation is the statistical relationship between the signals. We acclaim that the information reaching the sink is with certain contortion which should satisfy the user requirement, i.e. the accuracy threshold in our case. The contortion function is the composition of the signal magnitude along with the variance between the SNs. The various combinations between the variance and the signal magnitude results in higher or lower contortion.

TABLE I: Important notations and their meanings

| | |
|---|---|
| $CA$ | The contortion accuracy is the spatial accuracy reflecting how close is the achieved phenomenon distribution to the real world |
| $CE$ | The contortion experienced is the perceived contortion accuracy of sampling by the application/user/sink |
| $CR$ | The contortion required is the desired contortion accuracy of sampling by the application/user/sink |
| $Fi_{acc}$ | The fidelity is the lower bound for the expectation that the contortion experienced ($CE$) is equal or less than the contortion required $CR$ |
| $R$ | Transport reliability is the average success probability of the information to reach the sink |
| $L$ | Transport timeliness is the time needed for the samples to reach the sink |

A minimum set of spatial samples is required to reconstruct the information on the sink. To this end, SNs sample this spatial phenomenon and transmit their samples towards the sink. We assume that the sampling SNs have different sampling qualities. Apart from detecting the hotspot with certain accuracy, we also consider that the information reaching the sink is with certain reliability and timeliness. We assume that the link quality differs amongst the SNs and even the number of hops ($h$) to the sink from the source are different on each path. We assume that the most strict user requirements do not exceed the maximal capacity of the WSN [11].

### A. Problem Formulation and Objectives

Given a specific requirement $CR$ that is satisfied with certain contortion accuracy $CA$, the application actually expects exactly $CE$ = $CA$ at the sink. However, this guarantee is hard to be satisfied in WSNs due to the reliability of information transport. More precisely, due to this information loss $\Delta_{acc}$ the experienced contortion $CE$ will always be worse than the contortion at the source, i.e. $CE = CA + \Delta_{acc}$. On the other hand, instead of strict requirements we assume the application requires to meet the requirements with certain fidelity $Fi_{acc} \in [0,1]$ gearing it more towards the probabilistic nature of WSNs. Hence, the requirement at the source is to satisfy $P(CE \leq CR) \geq Fi_{acc}$.

Generating only required samples for satisfying $CR$ and delivering all of them to the sink would require a large number of retransmissions. Preliminary investigations [13] have shown that by slightly increasing the number of generated samples we can significantly reduce the total number of transmissions needed. However, sending too many additional samples will finally result in unnecessary high number of retransmissions which hinders timeliness. As the key goal, we aim to find the optimal number of additional samples and the optimal retransmissions per hop ($\#ret_h$) that result in a minimal number of total retransmissions and satisfy all requirements.

Summarizing, we can formulate the co-design as:

$$Min\{C(\#ret_{total}) : CA, R, L\}$$

More precisely, the cost function $C$ can be expressed depending on the individual network characteristics and the application requirements such that the total number of retransmissions ($\#ret_{total}$) are minimized.

## IV. Analysis of Sampling and Transport Co-Design

In this section, we analytically express the reliability, timeliness and accuracy.

### A. Reliable Information Transport

Reliability builds on the link quality of each hop. Therefore, let $RH_h$ be the Bernoulli variable indicating the successful delivery of a message at hop $h$ with probability

$$\mathbf{P}\{RH_h = 1\} = 1 - (1 - l_h)^{\#ret_h} \tag{1}$$

where $l_h$ is the link quality and $\#ret_h$ the maximum number of transmissions attempts at hop $h$. Then, $RP_p$ is 1 if the sample traversing path $p$ arrives at the sink and 0 otherwise. Thus,

$$\mathbf{P}\{RP_p = 1\} = \prod_{h \in H_p} \mathbf{P}\{RH_h = 1\}$$
$$\mathbf{P}\{RP_p = 1\} = \prod_{h \in H_p} (1 - (1 - l_h)^{\#ret_h}). \tag{2}$$

Here $H_p$ specifies the hops taken on path $p$. Let the information reliability $RI$ be the Bernoulli variable that is 1 if and only if all the sent samples arrive at the sink.

$$\mathbf{P}\{RI = 1\} = \prod_{p \in P} \mathbf{P}\{RP_i = 1\}$$
$$\mathbf{P}\{RI = 1\} = \prod_{p \in P} \prod_{h \in H_p} (1 - (1 - l_h)^{\#ret_h}) \tag{3}$$

Note that reliability depends on the link quality and the number of retransmissions at each hop, however, only the latter can be tuned in deployed networks.

### B. Maintaining the End-to-End Timeliness

To satisfy the required timeliness, we need a mechanism to perform per-hop decisions. Usually, the per-hop deadline computation can follow a constant, increasing or decreasing function. A constant function allocates the end-to-end deadline evenly to all the hops from the source to the sink, implicitly assuming that a packet would suffer the same delay at each hop. Intuitively, in a converge cast network, the closer a node to the sink, the greater will be the traffic that the node has to forward towards the sink. Thus, the longer will be the delay that a packet will suffer at nodes closer to the sink. Accordingly, a longer hop deadline should be assigned for the hops closer to the sink. The growth of deadlines can be then either linear, polynomial or exponential.

Considering both contention effects above, the hop deadline allocation can be calculated as an exponential decrease with the distance from the source ($\epsilon * e^{-\alpha*(h-h_i)}$) and an exponential increase towards the sink ($e^{\alpha*h_i}$). Accordingly, we propose to compute the tolerable latency on hop $h_i$ using Eq. (4)

$$L = \frac{\epsilon * e^{\alpha*(-h_i+(h/2))} + e^{\alpha*(h_i-(h/2))}}{\tau} + \beta \tag{4}$$

$\epsilon \in$ [0.5,1] is a constant to address the fact that deadlines at the sink should be higher than at the source; $\alpha$ is a constant to control the gradient of increase/decrease; $\beta$ is the minimum deadline that should be allocated to a hop; $\tau$ is the time scale factor to be able to select deadlines so that $\sum_{i=1}^{h} L_{h_i} = L$.

### C. Accurately Representing the Physical Phenomenon

The notion of sampling accuracy is chosen as the contortion function to accurately represent the spatial phenomenon. Sampling accuracy in this work is defined by the $CA(M)$ function as expressed in Eq. (5).

$$CA(M) = \sigma_s^2 - \frac{\sigma_s^4}{M(\sigma_s^2 + \sigma_N^2)}(2\sum_{i=1}^{M}\rho(s,i) - 1) + \frac{\sigma_s^6}{(M)^2(\sigma_s^2 + \sigma_N^2)^2}\sum_{i=1}^{M}\sum_{j\neq 1}^{M}\rho(i,j) \tag{5}$$

As according to the study [12], more the contortion function value, less is the accuracy. The sampling accuracy function mainly depends on $M$, $\sigma$ and $\rho$. As according to our problem formulation, the contortion accuracy $CA(M)$ has to always satisfy the contortion required $CR$ ($CA(M) < CR$ ), which is the threshold value/application requirement. In order to investigate the contortion achieved when smaller number of nodes sending information, we assume that only $M$ out of $N$ packets are received by the sink, where $N$ is the total number of SNs in the event area. However, considering the information transport, it is not trivial that we always receive the $M$ packets at the sink. In addition, due to the packet loss we always make the information out of scope for the application. On the other hand, if the contortion accuracy is not satisfied and the reliability of information transport of the packets is never determined, the considered spatial phenomenon at the source cannot be represented according to the ground truth at the sink.

### D. Mapping the Accuracy and Reliability Requirements

Considering just the contortion accuracy from Eq. (5) and the drawback of loss of packets in information transport, we now wire the reliability with the contortion accuracy.

$$CE(M) = \sigma_s^2 - \frac{\sigma_s^4}{E[X](\sigma_s^2 + \sigma_N^2)}(2\sum_{i \in M}(\rho(s,i) - 1) \cdot RP_i) + \frac{\sigma_s^6}{E[X]^2(\sigma_s^2 + \sigma_N^2)^2}\sum_{i \in M}\sum_{j \in M\setminus\{i\}}\rho(i,j) \cdot RP_i \cdot RP_j$$

However, as according to the problem formulation we need to satisfy $P(CE \leq CR) \geq Fi_{acc}$.

$$
\begin{aligned}
&\mathbf{P}(CE \leq CR) \\
&= \mathbf{P}\left\{\sigma_s^2 - \frac{\sigma_s^4}{E[X](\sigma_s^2+\sigma_N^2)}(2\sum_{i\in M}(\rho(s,i)-1)\cdot RP_i) \right. \\
&\left. + \frac{\sigma_s^6}{E[X]^2(\sigma_s^2+\sigma_N^2)^2} \sum_{i\in M}\sum_{j\in M\setminus\{i\}} \rho(i,j)\cdot RP_i \cdot RP_j \leq CR \right\} \\
&= ... \\
&= \sum_{(x_1,...,x_{|M|})\in\{0,1\}^{|M|}} \\
&\mathbf{P}\left\{\sigma_s^2 - \frac{\sigma_s^4}{E[X](\sigma_s^2+\sigma_N^2)}(2\sum_{i\in M}(\rho(s,i)-1)\cdot x_i) \right. \\
&\left. + \frac{\sigma_s^6}{E[X]^2(\sigma_s^2+\sigma_N^2)^2} \sum_{i\in M}\sum_{j\in M\setminus\{i\}} \rho(i,j)\cdot x_i \cdot x_j \leq CR \right\} \\
&\cdot \prod_{i=1}^{n} \mathbf{P}\{R_i = x_i\}
\end{aligned}
$$

Here X is a random variable for the number of samples received at the sink. The particular values which X can take are denoted by the corresponding combination of the $x_n$'s which in turn describe one particular combination of active nodes (i.e., node $n$ is activated iff $x_n = 1$).

Furthermore,

$$E[X] = \sum_{n=1}^{|M|} n \cdot \mathbf{P}(X = n)$$

and

$$\mathbf{P}(X = n) = \sum_{(i,j)\in C(|M|,n)} \prod_i \mathbf{P}(RP_i = 1) \prod_j \mathbf{P}(RP_j = 0)$$

where $C(|M|, n)$ is a set of tuples of sets, the first of each denoting a particular combination of indices for $n$ successful paths and the second denoting the corresponding combination of indices of $|M| - n$ unsuccessful paths.

## V. Multi-attribute Sampling and Information Transport Co-design

Now, let $M$ be the set of nodes available in the area of interest. Let $x_i, i \in M$ be 1 if node $i$ will send its sample via path $P_i$ and 0 otherwise, where $P_i$ is the set of all nodes on the path from $x_i$ to the sink. The function $p(i) = \sum_{h\in P_i} \#ret_h$ computes the number of retransmissions on the path the sample sent by node $i$ will require. Let $z_k, k = 0, ..., 2^{|M|} - 1$ be 1 if the particular combination $(x_i x_{i-1} ... x_1 x_0)$ of the ordered $x_i$ values corresponding to the binary representation of k satisfies the accuracy requirement and 0 otherwise. Thus,

$$
\begin{aligned}
z_k = 1 \Leftrightarrow \sigma_s^2 &- \frac{\sigma_s^4}{E[X](\sigma_s^2+\sigma_N^2)}(2\sum_{i\in M}(\rho(s,i)-1)\cdot r_i) \\
&+ \frac{\sigma_s^6}{E[X]^2(\sigma_s^2+\sigma_N^2)^2} \cdot \sum_{i\in M}\sum_{j\in M\setminus\{i\}} \rho(i,j)\cdot r_i \cdot r_j \\
\leq CR &
\end{aligned}
$$

Using these notations and the constraints derived in the prior sections, we find the following optimization problem:

$$
\begin{aligned}
&\text{Minimize} \sum_{i\in M} x_i \cdot p(i) \\
&\text{subject to} \\
&\sum_{k=0}^{2^{|M|}-1} \left( z_k \cdot \prod_{i=1}^{|M|} \mathbf{P}\{R_i = x_i\} \right) && \geq Fi_{acc} \\
&max\{\sum_{h\in P_p} d \cdot \#ret_h\} && \leq L
\end{aligned}
$$

### A. Analytical Evaluation

This section gives us the basis for the approach of the co-design and shows that there is always an impact on attributes when varying just one of them.

Fig. 3 shows how the path reliability is impacted by different number of retransmissions per hop. As it is intuitive, a higher number of retransmissions can maintain a higher reliability. Accordingly, in Fig. 3 it can be seen that the probability that all sent samples arrive at the sink decreases with increasing number of samples. However, this notion of information reliability is no suitable metric for representing the user's requirements.

Similarly, Fig. 4 show the impact of network topology and varying number of retransmission on the fidelity achieved at the sink. While in the practical scheme, fidelity is given as a fixed requirement, we chose this representation to emphasize the impact of different parameters on the experienced sampling quality. Here each bar denotes analysis of a random network setup. As it can be seen, differences in network setup have more than just statistical impact. In a nutshell, efficiency and accuracy are opposed properties, as efficiency decreases when accuracy is increased.

## VI. Generic Holistic Co-design Algorithm

In the following, we present generic holistic co-design algorithm in generalized WSNs. After the phenomenon detection and notification from the source to the sink, the sink immediately knows about the important properties such as link reliability, hop count (together implying $L$) and $M$, e.g. by a $n$-hop neighbor restricted hello-protocol. $\sigma$ and $\rho$ are specified by knowledge about the phenomenon. Fidelity and contortion accuracy requirements are provided by the user or the application and always accessible to the sink (Line 5-8 in Alg. 1).

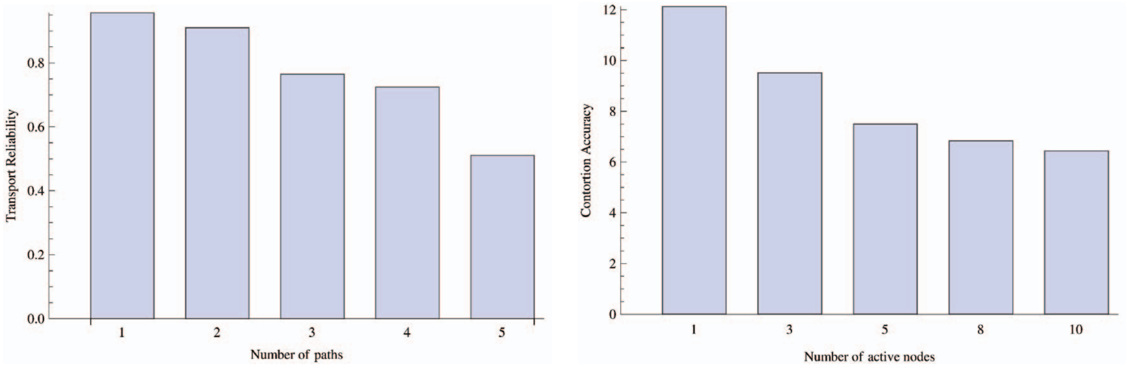


Fig. 3: Impact of network size on attained transport reliability (top left) and contortion accuracy (top right)

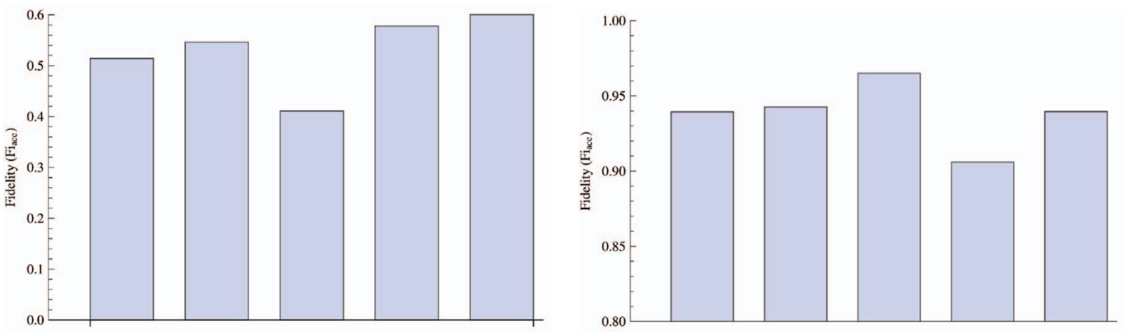


Fig. 4: Impact of different network setups on the achieved fidelity. Top left figure: (n = 10, CR = 30, hops $\in_R$ {4,5,6}, $\#ret_h \in_R$ {2,3}). Top Right figure: (n = 12, CR = 50, hops $\in_R$ {3,5,7}, $\#ret_h \in_R$ {3,4})

**Algorithm 1** : Generic Holistic Co-desing Algorithm ($GHC$ Alg.)

```
1: Const: CR, M, σ, ρ, Fi_acc
2: Var: CE, #ret_h, h, R, L, x_i, N
3: ----------------------------
4: /*Sampling SN → Sampling with CE:*/
5: /*After the phenomenon detection:*/
6: if SN_i in phenomenon area then
7:     Transmit msg (sample, h, R, M) to the sink
8: end if
9:
10: /*Sink solves the optimization problem*/
11:     Min(x_i · p(i)) s.t.
12:     (P(CE ≤ CR) ≥ Fi_acc
13:     max(LP_i) ≥ L)
14:     Transmit msg (ret_h, N) to the source
15:
16: /*Sampling SN → Upon receiving msg:*/
17: while active neighbors ≤ |N| do
18:     activate neighbor nodes
19: end while
20:
21: for SN_i in network do
22:     /*Upon receiving a data message msg */
23:     if msg is activation message then
24:         sample ← doSampling();
25:     else
26:         sample ← NULL;
27:     end if
28:     reply with ACK
29:     GHC.transport(msg, SN_i, sample);
30:     Exit();
31: end for
32:
33: /*Function GHC.transport()*/
34: GHC.transport(msg, SN, sample) {
35:     #ret_h ← msg.getRetrans(SN.getId());
36: if sample != NULL then
37:     msg.setSampleData(sample);
38: end if
39: for (r = 0; r ≤ #ret_h; r++) do
40:         Forward msg to next hop;
41:         wait for ACK or expiration;
42: end for
43: }
```

We consider the sink to know the application requirements concerning the sampling and information transport. Moreover, the requirement $(P(CE \leq CR) \geq Fi_{acc})$ is the key aspect to be solved by the sink. As the basic step, the sink solves the optimization problem constrained by $Fi_{acc}$ and determines the optimal parameters (set of active nodes $N$; $ret_h, \forall h \in P_i, \forall i \in N$) for the given network state (Line 11-13 in Alg. 1). The attained optimal values are reliably transmitted to the sources in the phenomenon area (Line 14 in Alg. 1). The overhead induced by the reliable communication is negligible since only a single message has to be transported reliably.

As for the information transport, upon receiving the data message, each SN forwards the controlling information including the sample value if selected for sampling (Line 32-30 in Alg. 1). Note that no information regarding timeliness is needed to be distributed since it is implicitly satisfied by applying the optimal number of retransmissions on the selected paths. The information transport is handled with $GHC$ transport function (Line 34-42 in Alg. 1).

## VII. Performance Evaluation

We evaluate our approach based on simulations in TOSSIM [7]. Optimization and visualization of analytical results was conducted using Wolfram Mathematica [10].

### A. Simulation Environment and Studies

We simulate between 20 to 200 SNs in an area of 75×75 unit$^2$ which is partitioned in a grid topology. The sink is located at one corner. The information is generated from the phenomenon area and transported towards the sink. The timeliness is measured in *ms*. We perform simulations for different

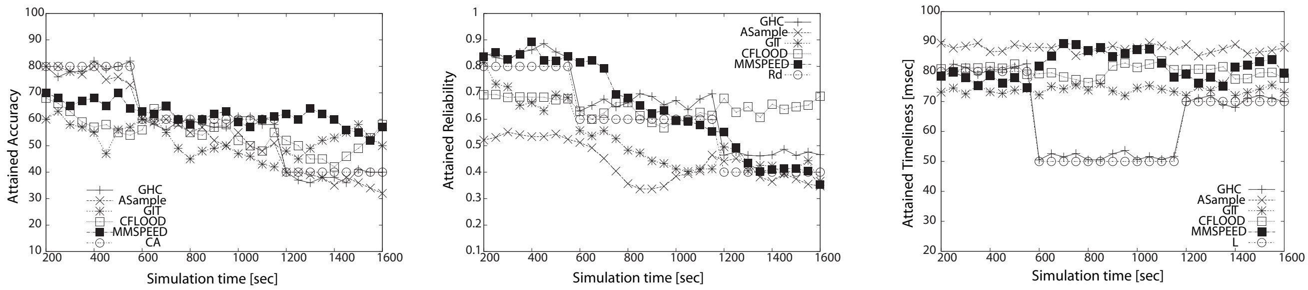


Fig. 5: Tunability for varying desired accuracy, reliability and timeliness

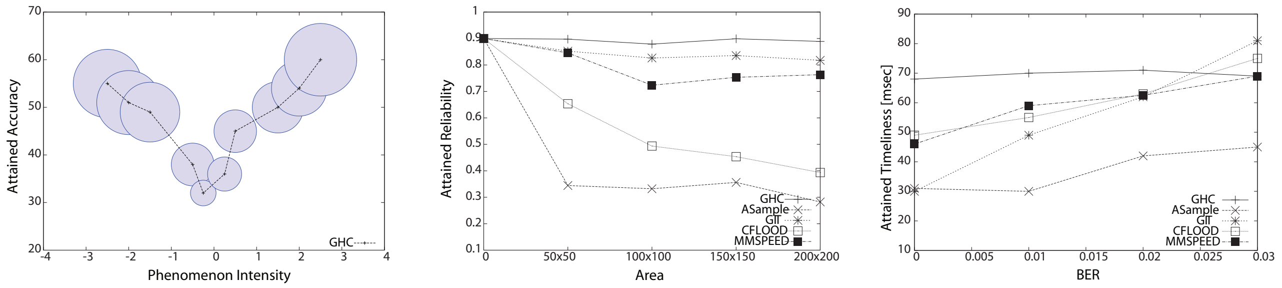


Fig. 6: Top left figure: Impact of phenomenon on attained accuracy, top middle figure: impact of area on attained reliability and top right figure: impact of BER on attained timeliness

combinations of $CA$, $R$ and $L$. The competitor protocols we have chosen are $ASample$ [5], $GIT$ [4], $CFLOOD$ [8] and $MMSPEED$ [1].

### B. Simulation Results

The application requirements for varying accuracy are $CA$ = 80, 60, 40, $R$ = 0.8 and $L$ = 60. The requirements on varying reliability are $CA$ = 80 $R$ = 0.8, 0.6, 0.4 and $L$ = 80. Finally, the requirements for varying timeliness are $CA$ = 70 $R$ = 0.6 and $L$ = 80, 50, 70.

Fig. 5 shows the tunability of accuracy. For the fair evaluation we have considered the definition of the contortion accuracy for compared protocols. We observe that $GHC$ attain the desired contortion accuracy with a slight difference than the user requirement. The attained reliability by $GHC$ is due to the achieved desired accuracy. The optimization function is combined with accuracy, reliability and timeliness, hence, any variation with the accuracy and reliability directly also affects the timeliness.

As observed in Fig. 6, the accuracy has a desired effect with the center of the phenomenon and the contortion function increases while the phenomenon spreads. From Fig. 6 we can also observe that $GHC$ attains desired reliability with varying area. The rest of the competitor protocols just fails and lacks to satisfy the user required reliability. Fig. 6 also shows that other competitor protocols are independent from the desired timeliness and fail to cope with the co-design.

## VIII. Conclusion

Through this paper, we have provided the tunable co-design for optimizing the network performance. Through formulation of the optimization problem for sampling and transport co-design, we show the avoidance of over or under provision of information. In addition, we have maximized the efficiency and satisfied the evolvavable user requirements on accuracy, reliability and timeliness. For future work, we aim to consider the in-network processing techniques for co-design.

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