Some Improved and Generalized Estimation Schemes for Clock Synchronization of Listening Nodes in Wireless Sensor Networks

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Abstract—A sender-receiver paradigm, in which a master and slave node exchange timing packets to estimate the clock offsets of the slave node and other nodes located in the common broadcast region of master and slave nodes, is adopted herein for synchronizing the clocks of individual nodes in a wireless sensor network (WSN). The maximum likelihood estimate of the clock offset of the listening node hearing the broadcasts from both the master and slave nodes was derived in [1] assuming symmetric exponential link delays. This paper advances those results in two directions. First, some improved estimators, each being optimal in its own class, are derived for the clock offset of the listening node and mean link delays. Second, the results are generalized by addressing the more realistic problem of clock offset estimation under asymmetric exponential delays. The results presented in this paper are important for time synchronization of WSNs, where these techniques can be utilized to achieve accurate clock estimates with reduced power consumption.

Index Terms—Clock, synchronization, wireless sensor network.

I. INTRODUCTION AND RELATED WORK

It is well known that energy is the scarcest resource in wireless sensor networks (WSN), and hence WSNs demand the power consumption issue as the primary feature around which their design, algorithms and analysis should be planned. In the recent past, WSNs have been deployed for many applications, e.g., habitat monitoring, security, surveillance, process control, traffic monitoring, fire detection, etc. Most of these applications require the nodes of the WSN to be synchronized in time, as is the case with object tracking, data fusion, localization, security protocols, efficient duty cycling, etc. Various protocols addressing the clock synchronization problem in WSNs are mainly based on packet synchronization techniques which can be divided into three fundamental approaches: sender-receiver synchronization as in [2], receiver-receiver synchronization like [3] or a hybrid of both schemes [4]. In the receiver-receiver (or hybrid) paradigm, when a master node broadcasts the timing packets, the silent nodes in the communication range of the broadcast can hear the synchronization messages, and then can estimate their individual clock parameters with low cost. The same technique can be exploited in the sender-receiver scenario [5] in WSNs owing to the wireless nature of the broadcast medium, where the nodes, located in the common broadcast region of a master and slave node, can overhear the time synchronization packets between them and exploit the received observations for synchronizing their clocks with the master node. In [1], the Maximum Likelihood Estimates (MLE) for the clock offset and mean link delays of the listening nodes were derived under the symmetric exponential delay model. This paper not only presents better estimation techniques relative to MLE, but also addresses the problem under the more realistic asymmetric delay model.

II. PROBLEM FORMULATION

Fig. 1 shows a WSN consisting of several nodes, with a master node \( r \) chosen as the reference clock node for the rest of that synchronization cycle. Node \( r \) can either have a connection with some external clock (e.g., GPS or a dedicated link) for synchronizing the network with real time, or its clock can just be used as a reference for internal network synchronization. According to the defined sender-receiver protocol, node \( r \) selects another node \( s \) as the slave node at the start of the synchronization cycle, whose clock offset is \( \psi_r \) with respect to node \( r \). As illustrated in Fig. 2, a simple two-way timing message exchange is performed \( N \) times between these two nodes, where \( k \) is the timing index.

It can be observed from Fig. 1 that for any geometrical shape for the transmission range of sensor nodes, a few other nodes (e.g., node \( t \) whose clock offset with respect to node \( r \) is \( \psi_t \)) lie within the intersection of the broadcast regions of nodes \( r \) and \( s \). These nodes can listen to the whole message exchange through the channel between nodes \( r \) and \( s \) and hence conserving considerable power, synchronize their clocks...
with the reference. Assume that node $t$ timestamps the timing cells coming from nodes $r$ and $s$ as $m_{k}^{rs}$ and $m_{k}^{rt}$, respectively, as illustrated in Fig. 2. Notice that node $t$ is also receiving the packets $m_{k}^{rs}$, sent by node $r$ and timestamped by node $s$, along with $m_{k}^{s}$ because node $s$ is required to send this information back to node $r$ inside the packet containing $m_{k}^{r}$.

There are different types of link delay uncertainties in the radio message delivery from the construction of the message at the transmitting node to its decoding at the receiving node, which might be much greater than the required tolerance of time synchronization. Therefore, it is very important to assess the nature and significance of all the components comprising these sources of error. Taking into account even the minutest details, [4] classified all the link delay uncertainties incurred by the message as either deterministic or nondeterministic. The sources of delays such as send time, channel access time, interrupt handling time, receive time, etc., are nondeterministic and can range from around 5 $\mu$s to 500 ms. On the other hand, there are deterministic sources of delays such as encoding time, transmission time, propagation time, reception time, decoding time, byte alignment time, etc., which can range from 0 $\mu$s to 20 ms. In addition, dividing the link delay uncertainties in deterministic and nondeterministic components is a standard technique in the network theory.

In this paper, it is assumed that the deterministic part of link delays is unknown but same for all the nodes receiving the messages from nodes $r$ and $s$. This is because usually the nodes in a WSN share the same hardware specifications and characteristics and hence undergo similar transmission, reception, encoding, decoding and byte alignment times. In addition, the propagation time of RF waveforms is less than 1 $\mu$s for ranges under 300 meters which implies that for nodes lying close by at short distances from each other, the difference in the propagation time of the same message will be even less than a few nano seconds. Therefore, the deterministic part of link delays is denoted as $\tau$ in this paper independent of the two nodes transmitting and receiving the timing packets. Moreover, the nondeterministic or random link delays, $\varepsilon_{k}^{rs}$, $\varepsilon_{k}^{sr}$ and $\varepsilon_{k}^{rt}$, are modeled as coming from the exponential distribution and both cases with similar and dissimilar means will be studied in detail. A vast discussion on the justifications behind these assumptions can be found in [6]. The following equations summarize the model depicted above for $k = 1, \ldots, N$.

\[
m_{k}^{rs} - m_{k}^{r} = U_{k} = \psi_{s}^{r} + \tau + \varepsilon_{k}^{rs},
\]
\[
m_{k}^{rt} - m_{k}^{r} = V_{k} = \psi_{s}^{t} + \tau + \varepsilon_{k}^{rt},
\]
\[
m_{k}^{s} - m_{k}^{s} = W_{k} = \psi_{s}^{o} + \tau + \varepsilon_{k}^{st},
\]

where $\varepsilon_{k}^{rs}$, $\varepsilon_{k}^{sr}$ and $\varepsilon_{k}^{rt}$ are independent and identically distributed exponential random variables with means $\alpha$, $\beta$ and $\gamma$, respectively. Based on this model with equal $\alpha$, $\beta$ and $\gamma$, the MLE derived in [1] is expressed as

\[
\hat{\Psi}_{S} = \begin{bmatrix}
\hat{\psi}_{s}^{t} \\
\hat{\psi}_{s}^{o} \\
\hat{\tau}
\end{bmatrix}
= \begin{bmatrix}
2V_{1} - U_{1} - W_{1} \\
V_{1} - W_{1} \\
U_{1} - V_{1} + W_{1}
\end{bmatrix},
\]

where the subscript $S$ points to the estimates being driven for symmetric link delays and the subscript $(1)$ denotes the minimum order statistics of their respective data sets.

### III. Asymmetric Link Delays

In most communications and wireless channels, and ad-hoc networks with time-varying topologies, the network delays are asymmetric in nature. Therefore, a study for deriving the efficient estimators in this case is of paramount importance. Let the order statistics of the observations $\{U_{k}\}_{k=1}^{N}$, $\{V_{k}\}_{k=1}^{N}$ and $\{W_{k}\}_{k=1}^{N}$ be denoted as $\{U_{(k)}\}_{k=1}^{N}$, $\{V_{(k)}\}_{k=1}^{N}$ and $\{W_{(k)}\}_{k=1}^{N}$, respectively. Transforming the data set as $U_{k}' \triangleq (U_{k} - \psi_{s}^{o} - \tau)/\alpha$, $V_{k}' \triangleq (V_{k} - \psi_{s}^{o} - \tau)/\beta$, and $W_{k}' \triangleq (W_{k} - \psi_{s}^{o} - \psi_{s}^{t} - \tau)/\gamma$, makes it a set of independent observations on the standardized variate and hence the distribution becomes parameter-free. The order statistics of $U_{k}'$, $V_{k}'$ and $W_{k}'$ are denoted by $U_{(k)}^{'}$, $V_{(k)}^{'}$ and $W_{(k)}^{'}$, respectively. Now it is straightforward to see that

\[
E[U_{(k)}] = \psi_{s}^{o} + \tau + \alpha E[U_{(k)}'],
\]
\[
var[U_{(k)}] = \alpha^{2} \cdot var[U_{(k)}'],
\]
\[
cov[U_{(k)}U_{(j)}] = \alpha^{2} \cdot cov[U_{(k)}U_{(j)}'].
\]

Similar relations hold between $\{V_{(k)}^{'}\}$ and $\{W_{(k)}^{'}\}$. Next, utilizing the statistics of the ordered samples $U_{(k)}^{'}$, $V_{(k)}^{'}$, $W_{(k)}^{'}$ see [7]), the $N \times N$ symmetric positive-definite covariance matrix $C$ for each of $U_{(k)}^{'}$, $V_{(k)}^{'}$ and $W_{(k)}^{'}$ takes the form:

\[
C = \begin{bmatrix}
\frac{1}{N} & \frac{1}{N^{2}} & \ldots & \frac{1}{N^{2}} \\
\frac{1}{N} & \frac{1}{N^{2}} + \frac{1}{(N-1)^{2}} & \ldots & \frac{1}{N} + \frac{1}{(N-1)^{2}} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{1}{N} & \frac{1}{N^{2}} + \frac{1}{(N-1)^{2}} & \ldots & \frac{1}{N^{2}} + \sum_{k=1}^{N} \frac{1}{(N-k+1)^{2}}
\end{bmatrix}.
\]

The inverse of this covariance matrix is found through the Gauss-Jordan elimination method. Next we proceed towards estimating the clock parameters and mean link delays.

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Fig. 2. Timing message exchange between nodes $r$ and $s$, which node $t$ is also receiving.
A. Best Linear Unbiased Estimation Using Order Statistics

It is well known that the derivation of regular BLUE for a problem yields suboptimal results in general, since the class of unbiased estimators within which the search is performed is restricted to be linear. However, for a general location-scale distribution, [8] suggested a technique based on the derivation of BLUE using order statistics instead of just the raw observations. This technique will be exploited in the scenario addressed in this paper.

Let $\Psi_A \triangleq \begin{bmatrix} \psi_1 & \psi_2 & \cdots & \psi_N \end{bmatrix}^T$, where the subscripts A denotes the relevance of estimators to asymmetric link delays and $z \triangleq [U(1)_T U(2)_T \cdots U(N)_T V(1)_T V(2)_T \cdots V(N)_T W(1)_T W(2)_T \cdots W(N)_T]^T$, then the linear model based on the ordered observations can be expressed as

$$E[z] = Q\Psi_A,$$

where $Q$ is a known matrix of dimension $3N \times 6$, whose elements relate the ordered data with its standardized ordered form. Since the model is linear in terms of the ordered observations, the BLUE can be expressed as

$$\hat{\Psi}_A = (Q^TC_z^{-1}Q)^{-1}Q^TC_z^{-1}z,$$

where $C_z$ is the joint covariance matrix for $U(k)_T$, $V(k)_T$ and $W(k)_T$. The notation $\text{diag}\{\cdot\}$ denote a diagonal matrix. Due to the mutual independence between these data sets, $C_z$ can be expressed as $C_z = \text{diag}\{\alpha^2C, \beta^2C, \gamma^2C\}$, and its inverse is $C_z^{-1} = \text{diag}\{\alpha^{-2}C^{-1}, \beta^{-2}C^{-1}, \gamma^{-2}C^{-1}\}$. Based on the above expression, we get (5). (See top of next page.) Using the above relations, $\hat{\Psi}_A$ can be found to be equal to (6). (See top of next page.)

B. Minimum Variance Unbiased Estimation

Restricting the possible estimators to be unbiased and then finding the estimator with the smallest variance for all values of the unknown parameter is a common practice in estimation theory that yields the optimal solution within the class of unbiased estimators. Hence, we proceed towards deriving the MVUE for the clock offset and mean link delays for the problem at hand utilizing Rao-Blackwell-Lehmann-Scheffé theorem.

In the asymmetric delays case, the likelihood function for the clock offset as a function of observations $\{U(k)\}_{k=1}^N$, $\{V(k)\}_{k=1}^N$ and $\{W(k)\}_{k=1}^N$ is given by (7) at the top of the next page, where $I(\cdot)$ denotes the unit step function. Exploiting the Neyman-Fisher factorization theorem and the fact that the raw sample mean and the ordered sample mean are actually the same, it is straightforward to see that $T = \{\sum_{k=1}^N U(k)_T, U(1)_T, \sum_{k=1}^N V(k)_T, V(1)_T, \sum_{k=1}^N W(k)_T, W(1)_T\}$ is a sufficient statistic for $\Psi_A$. Since the probability density function (pdf) of $T$ is required to check whether $T$ is complete, and $\sum_{k=1}^N U(k)_T$ and $U(1)_T$, $\sum_{k=1}^N V(k)_T$ and $V(1)_T$, and $\sum_{k=1}^N W(k)_T$ and $W(1)_T$ are independent, we proceed as follows. Considering into account only the data set $\{V(k)\}_{k=1}^N$ first, it is evident that the pdf of the minimum order statistic $V(1)_T$ is exponential with mean $\beta/\gamma$, whereas the joint pdf of $V(1)_T, V(2)_T, \ldots, V(N)_T$ is given by (8). (See top of next page.)

Now consider the transformation as in [7],

$$\eta_k = (N - k + 1) (V(k) - V(k-1)), \quad k = 1, 2, \ldots, N,$$

where $V(0) = \psi_0 + \tau$. Since $\sum_{k=1}^N (V(k) - \psi_0 - \tau) = \sum_{k=1}^N \eta_k$ and the Jacobian of the transformation is $N!$, a substitution in (8) reveals that

$$p(\eta_1, \eta_2, \ldots, \eta_N) = \beta^{-N} e^{-\frac{N}{\beta} \sum_{k=1}^N \eta_k}, \quad \prod_{k=1}^N I[\eta_k],$$

i.e., $\eta_k$ are independent exponential RVs with similar mean $\beta$. In addition, since each $\eta_k \sim \exp(\beta)$, each $\eta_k$ also assumes a Gamma distribution $\eta_k \sim \Gamma(1, \beta)$. Using the relationship $\sum_{k=1}^N (V(k)_T - V(1)_T) = \sum_{k=1}^N \eta_k$, and the fact that each of $\eta_2, \eta_3, \ldots, \eta_N$ is independent of $\eta_1$ (and hence of $V(1)_T$, since $\eta_1 = N(V(1)_T - \psi_0 - \tau)$), $\sum_{k=1}^N (V(k)_T - V(1)_T) \sim \Gamma(N - 1, \beta)$ and is independent of $V(1)_T$.

By a similar reasoning, it can be deduced that $\sum_{k=1}^N (U(k)_T - U(1)_T) \sim \Gamma(N - 1, \alpha)$, and $\sum_{k=1}^N (W(k)_T - W(1)_T) \sim \Gamma(N - 1, \gamma)$, and are independent of $U(1)_T$ and $W(1)_T$, respectively. Therefore, the one-to-one function $T' = \{\sum_{k=1}^N (U(k)_T - U(1)_T), U(1)_T, \sum_{k=1}^N (V(k)_T - V(1)_T), V(1)_T, \sum_{k=1}^N (W(k)_T - W(1)_T), W(1)_T\}$ of $T$ is also sufficient for estimating $\Psi_A$ because the sufficient statistics are unique within one-to-one transformations. Consequently, $T'$ comprises six independent random variables, which in terms of the three-parameter Gamma distribution are given by

$$u = \sum_{k=1}^N (U(k)_T - U(1)_T) \sim \Gamma(N - 1, \alpha, 0),$$

$$U(1)_T \sim \Gamma(1, \alpha/N, \psi_0^* + \tau),$$

$$v = \sum_{k=1}^N (V(k)_T - V(1)_T) \sim \Gamma(N - 1, \beta, 0),$$

$$V(1)_T \sim \Gamma(1, \beta/N, \psi_0^* + \tau),$$

$$w = \sum_{k=1}^N (W(k)_T - W(1)_T) \sim \Gamma(N - 1, \gamma, 0),$$

$$W(1)_T \sim \Gamma(1, \gamma/N, \psi_0^* - \psi_0^* + \tau).$$

Note that the domains of $u, v$ and $w$ are controlled by $U(1)_T$, $V(1)_T$ and $W(1)_T$, respectively. Next, it has to be checked whether $T'$, or equivalently $T$, is complete. Completeness implies that there is but one function of $T$ that is unbiased. Let $g(T')$ be a function of $T'$ such that $E[g(T')] = \Psi_A$. Suppose that there exists another function $h$ for which $E[h(T')] = \Psi_A$ is also true. Then,

$$E\left[g\left(T'\right) - h\left(T'\right)\right] = E\left[\pi\left(T'\right)\right] = 0 \quad \forall \Psi_A,$$

where $\pi(T') \triangleq g(T') - h(T')$ and the expectation is taken with respect to $p(T'; \Psi_A)$. As a result, see the equation at the bottom of the next page, where $R_{U(1)_T, V(1)_T, W(1)_T}$ is the region defined by $I(U(1)_T - \psi_0^* - \tau), I[V(1)_T - \psi_0^* - \tau]$ and $I[W(1)_T - \psi_0^* + \psi_0^* - \tau]$. Rearranging the above, we find that the left side of the above equation is the six-dimensional Laplace transform of $\pi(T')$. It follows from the uniqueness theorem for two-sided Laplace transform that $\pi(T') = 0$ almost everywhere, leading to $g(T') = h(T')$ and hence there is only one unbiased function of $T$. This proves that the statistic $T'$, or equivalently $T$, is complete for estimating $\Psi_A$ when the links are asymmetric and all of $\alpha, \beta$ and $\gamma$ are unknown. Finally, the complete sufficient statistic $T$ is
\[
\begin{bmatrix}
\alpha^2 + 4\beta^2 + \gamma^2 & 2\beta^2 + \gamma^2 & - (\alpha^2 + 2\beta^2 + \gamma^2) & \alpha^2 - 2\beta^2 & \gamma^2 \\
2\beta^2 + \gamma^2 & \beta^2 + \gamma^2 & - (\beta^2 + \gamma^2) & 0 & -\beta^2 & \gamma^2 \\
- (\alpha^2 + 2\beta^2 + \gamma^2) & - (\beta^2 + \gamma^2) & - (\alpha^2 + \beta^2 + \gamma^2) & 0 & 0 & -\gamma^2 \\
\alpha^2 & 0 & 0 & -\alpha^2 & \beta^2 & 0 \\
-2\beta^2 & -\beta^2 & \beta^2 & 0 & N\beta^2 & 0 \\
\gamma^2 & \gamma^2 & 0 & 0 & 0 & N\gamma^2 \\
\end{bmatrix}
\]

\[\hat{\Psi}_A = \begin{bmatrix}
\hat{\psi}_t^\alpha \\
\hat{\psi}_o^\alpha \\
\hat{\tau} \\
\hat{\alpha} \\
\hat{\beta} \\
\hat{\gamma}
\end{bmatrix} = \frac{1}{N-1} \begin{bmatrix}
N (2V_1 - U_1 - W_1) - (2\overline{V} - \overline{U} - \overline{W}) \\
N (V_1 - W_1) - (\overline{V} - \overline{W}) \\
N (U_1 - V_1 + W_1) - (\overline{U} - \overline{V} + \overline{W}) \\
N (\overline{U} - U_1) \\
N (\overline{V} - V_1) \\
N (\overline{W} - W_1)
\end{bmatrix}
\]

\[L(\psi_t^\alpha, \psi_o^\alpha, \tau, \alpha, \beta, \gamma) = (\alpha \beta \gamma)^{-N} e^{-\frac{\gamma}{2} \sum_{k=1}^{N} \left( V_k - \psi_t^\alpha - \tau \right)} \left( \sum_{k=1}^{N} \left[ V_k - \psi_t^\alpha - \tau \right] \right) \times \left( \prod_{k=1}^{N} \left[ V_k - \psi_o^\alpha - \tau \right] \right).
\]

\[f(V_1, V_2, \ldots, V_N) = N! \beta^{-N} e^{-\frac{\gamma}{2} \sum_{k=1}^{N} \left( V_k - \psi_t^\alpha - \tau \right)} \left( \prod_{k=1}^{N} \left[ V_k - \psi_o^\alpha - \tau \right] \right).
\]

also minimal owing to Bahadur’s theorem which states that if \( \mathbf{T} \) taking values in \( \mathbb{R}^k \) is sufficient for \( \Psi_A \) and boundedly complete, then \( \mathbf{T} \) is minimal sufficient.

Consequently, finding an unbiased estimator for \( \Psi_A \) as a function of \( \mathbf{T} \) yields the MVUE, according to the Rao-Blackwell-Lehmann-Scheffé theorem. Noting that the ordered BLUE \( \hat{\Psi}_A \) in (6) is an unbiased function of \( \mathbf{T} \), it is concluded that it is also the MVUE. The covariance matrix of this estimator is given by (5) and hence the variances (or MSEs) of the clock offsets, fixed and mean delay parameters are given by its diagonal elements, whereas the total MSE for the vector parameter \( \hat{\Psi}_A \) is the trace of this matrix.

As a result, the MVUE for the desired parameter, the clock offset of the listening nodes, for asymmetric unknown network delays is expressed as

\[\hat{\psi}_o^t = \frac{1}{(N-1)} \left( N (2V_1 - U_1 - W_1) - (2\overline{V} - \overline{U} - \overline{W}) \right),\]  

and its variance, equal to its MSE, is

\[\text{var}(\hat{\psi}_o^t) = \frac{1}{(N-1)} (\alpha^2 + 4\beta^2 + \gamma^2).\]

C. Minimum Mean Square Error Estimation

Finding the MMSE estimator is not a straightforward task in any scenario, but [9] described a method to find the estimator for linear functions of the location and scale parameters with smallest mean square error among estimators with expected loss independent of the location parameters (clock offset and fixed portion of delay in the current problem). Generalizing those results, the MMSE estimators of the clock offsets and fixed delay parameter are given by the equation at the top of the next page. Therefore, the MMSE estimator for the clock offset of the listening node is expressed as

\[\hat{\psi}_o^t = \frac{1}{N} \left[ (N+1) (2V_1 - U_1 - W_1) - (2\overline{V} - \overline{U} - \overline{W}) \right],\]
and its mean square error is given by
\[
\text{MSE}(\hat{\psi}_o) = \frac{N + 1}{N^3} \left( \alpha^2 + 4\beta^2 + \gamma^2 \right),
\]
which clearly outperforms the MVUE. The performance of the three estimators, namely the MLE, MVUE and MMSE, has been simulated in Fig. 3 with the number of timestamps \(N = 5 : 10\), deterministic delay \(\tau = 0.5\), the clock offset of the listening node \(\psi_o = 1.0005\), the exponential delay parameters \(\alpha = 2\), \(\beta = 0.5\alpha\) and \(\gamma = 1.5\alpha\). It is evident from the curves that the MVUE and MMSE perform better than the MLE, as the advantage of MVUE over MLE obviously is from its basic principles (cost functions) and there is no bias associated with MVUE.

### IV. Symmetric Link Delays

The symmetric network delay assumption holds true for some scenarios, e.g., when the nodes have a direct communication link between them and the topology of the network is constant. In this case, \(\alpha = \beta = \gamma = \lambda\). Then, using the same methodology as adopted in Section III, the BLUE based on order statistics in the symmetric exponential delays case is given by
\[
\hat{\Psi}_S = \frac{1}{3(N-1)} \left\{ \frac{2V(1) - U(1) - W(1)}{2V(1)} + \frac{3N(U(1) + W(1) - V(1))}{2V(1) - W(1)} + \frac{2(V(1) - U(1) - W(1))}{2V(1) - W(1)} \right\}
\]

Similarly, the MVUE is identical to BLUE and hence, the MVUE for the clock offset of the listening node, in the case of symmetric delays, is given by
\[
\hat{\psi}_o = 2V(1) - U(1) - W(1),
\]
and its variance can be expressed as \(\text{var} (\hat{\psi}_o) = 6\lambda^2/N^2\). Finally, the MMSE estimator for the clock offset of the listening nodes is the same as the MLE, ordered BLUE and MVUE for the symmetric exponential delay model.

### V. Conclusions

In this paper, three different parameter estimation schemes are employed to accomplish the goal of accurately synchronizing a wireless sensor network. The results provided here not only apply the above mentioned better schemes to the clock synchronization problem as compared to the MLE derived previously in [1], but also generalize its scope by taking into account the realistic asymmetric link delays scenario. These findings are very useful in the realm of wireless sensor networks, where many applications demand tight synchronization among the clocks of the nodes while spending the power as less as possible.

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### REFERENCES


