Theoretical Estimators and Lower-Bounds for Receiver-to-Receiver Time Synchronization in Multi-Hop Wireless Networks

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***Abstract*—Maximum likelihood estimators (MLE) for time synchronization parameters of receiver-to-receiver protocols are derived. The MLE are first provided for a single-hop model, then generalized to a multi-hop model. The appropriate Cramer-Rao lower bounds (CRLB) for the estimators are then derived, which serves as a theoretical lower bound to any unbiased estimator. The proposed estimators are compared with their respective CRLB through simulation in multi-hop scenarios of up-to eight hops. The results show fast convergence of the estimation precision to the CRLB and demonstrate a high precision, where the mean square error (MSE) does not exceed 10^{-6} for the skew, and 10^{-5} for the offset.**

I. Introduction

Real applications of wireless communication networks require fine grained synchronization. Existing synchronization solutions can be divided into sender-to-receiver protocols vs. receiver-to-receiver protocols [1]. The Reference Broadcast Synchronization (RBS) protocol [2] introduces the receiver-to-receiver synchronization, which is completely different from the sender-to-receiver synchronization used by most of the state-of-the-art protocols [3]. It relies on the broadcast property of the wireless communication medium, where receivers located within listening distance to the same sender (reference) would physically capture a broadcast signal at approximately the same time.

RBS uses a sequence of synchronization signals (beacons) from a fixed sender (reference), which allows receiver nodes to estimate relative offsets/skews to their neighboring nodes. The reference periodically broadcasts signals that are received at the synchronizing nodes. Reception events are timestamped with local clocks, then they are exchanged between the nodes. They are used as samples for estimating relative skews/offsets. The protocol reduces the time-critical path, which is defined as the path of a message that contributes to non-deterministic errors [3]. With any sender-to-receiver protocol, the time involved in sending a message from a sender to a receiver is the result of the following four factors that can vary non-deterministically: i) Send time, which is the time spent by the sender for message construction along with the time spent to transmit the message from the sender's host to the network interface. ii) Access time; the time spent for medium access at the MAC layer. iii) Propagation time, as the time for the message to reach the receiver once it has left the sender's radio. iv) Receive time, which is the time spent by the receiver to process the message. RBS removes the send time and the access time from the critical path, which represent the two largest sources of non-determinism. This provides a high degree of synchronization accuracy. Still, timestamping may witness some variability due to the reception delays at the receivers.

Sari et al. [4] are the first to consider the joint offset/skew estimation for RBS protocol. They propose maximum likelihood estimators (MLE) and derive the Cramer-Rao lower bound (CRLB) for single-hop synchronization, assuming exponential distribution of reception delays. In this paper, Gaussian delays are considered, as it has been shown that the later distribution is more appropriate to RBS [2]. In fact, exponential model is more appropriate when delays include queueing time, which is typical when the sending delay is affecting the time critical path, i.e., sender-to-receive protocols. Although many solutions in the literature have already considered the joint skew/offset estimation in multi-hop networks, none has considered MLE and CRLB in such environment, which represents the contribution of this paper. Note that the work of Sari et al. [4] is limited to single-hop synchronization.

The reminder of the paper is organized as follows. The related work is presented in the next section, followed by the proposed one-hop model and estimators in Section III. Section IV gives the multi-hop model that extends the estimators. The CRLB of these estimators is derived in Section V, then the estimators are numerically evaluated and compared to their respective CRLB in Section VI. Finally, Section VII draws the conclusions.

II. Related Work

Many solutions have been proposed for time synchronization in wireless networks. We refer to [1] as a good introductive survey, and to [3], [5], [6] for more detailed and up-to-date reviews. Most of the protocols proposed thus far use send-to-receiver synchronization, where the synchronizing nodes exchange messages and use transmission and reception events to record timestamps. The timestamps are used as samples by the estimators. Some of these solutions allow nodes to run their clocks independently and define mechanisms to calculate (estimate) relative skews and/or offsets; This is know as relative synchronization. Noh et al. [7] consider local (one-hop) relative synchronization and provide general offset/skew MLE estimators for sender-to-receiver protocols, where only the first and the last observations are used. The approach was generalized in [8]. For single-hop estimation, a similar mathematical approach is followed in this paper. However, the model, and consequently all the derived estimators and bounds, are completely different. The model of [7] does not apply to RBS, as the latter is receiver/receiver-based. RAT [9] (Rate Adaptive Time synchronization) is another local sender-to-receiver synchronization protocol, which has been integrated with B-MAC [10] to incrementally improve its performance. Since the authors' aim was limited to reducing the preamble period at the MAC layer, the protocol provides a weak synchronization.

Instead of estimating relative offset/skew, some solutions define distributed mechanisms that allow nodes to update their clocks and converge to common values, i.e. continuous clock updates. In [11], [12], and [13] the authors propose solutions that deal with single, as well as multi-hop synchronization. These solutions have the gradient property and focus on local synchronization, i.e., high precision is provided for neighboring nodes (their clock values converge closely), whereas the precision decreases with the distance. In all clock-update solutions, nodes continuously update their local clocks. This update generally involves jump/freeze of the clock values, which may affect the correctness of local events' timestamping.

Contrary to gradient solutions, some other solutions focus on global synchronization and attempt to improve the multi-hop precision. He et al. [14] propose a global synchronization protocol based on spanning tree. Lenzen et al. [15] provide probabilistic lower bounds for multi-hop synchronization. Ferrari et al. propose Secondis [16], where they define strategies to disseminate synchronization messages (signals) from the root node to the whole network in a tree-based network structure. In [17] and [18], the authors propose other multi-hop-centric synchronization protocols. Rentel et al. [19] define a general multi-hop solution that applies to both MANET (mobile ad hoc networks) and WSN (wireless sensor networks). Kong et al. [20] deal with multi-hop synchronization by clustering the network. The protocol starts by synchronizing cluster-heads to the base-station, then cluster-heads synchronize regular nodes. In [21], Shames and Bishop propose a centralized approach to estimate clock relative offset where considering topology constraints. The basic idea is that in a cycle, the sum of all relative offsets must be null. The authors formulated the problem as a constrained optimization problem and resolved it using graph theory and the mean square deviation minimization.

As described previously, RBS [2] uses a completely different approach (receiver-to-receiver) that has the advantage of reducing the time-critical path. Lately, many solutions based on the receiver-to-receiver paradigm have been proposed [22], [4], [23], [24], [25]. Some of them consider MLE in the skew/offset model [4]. However, none considers MLE/CRLB in multi-hop networks, which represents the contribution of this paper.

III. One-hop Model and Estimators

Synchronization between two nodes, say, n_1 and n_2, is described, i.e., n_2's estimation of synchronization parameters relating its clock to that of n_1. The same process is to be applied for each pair of communicating nodes. Let u_i and v_i, where $i \in \{1, ..., K\}$, denote the i^{th} beacon reception timestamp of node n_1, and node n_2, respectively, and X_{ui}, X_{vi}, the corresponding reception delays. These delays are supposed to be Gaussian distributed (normal) random variables (rv) with the same parameters, i.e., $\sim \mathcal{N}(\mu, \sigma_0^2)$. Let us denote $X_{ui} - X_{vi}$ by X_i, and the relative skew and offset respectively by α and β. Application of the general linear equation relating two clocks to the model yields [3]: $u_i = \alpha v_i + \beta + X_i$. Therefore,

$$X_i = u_i - \alpha v_i - \beta, \tag{1}$$

Without loss of generality, assume a homogeneous network. X_i is thus the difference between two Gaussian rv with the same parameters, hence it is a zero-mean Gaussian rv; $X_i \sim \mathcal{N}(0, \sigma^2)$, where $\sigma^2 = 2\sigma_0^2$.

The likelihood function gathering K samples, $\mathcal{L}(\alpha, \beta | X_1, ... X_K)$, is given by,

$$\begin{aligned}\mathcal{L}(\alpha, \beta | X_1, ... X_K) &= \prod_{i=1}^{K} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-1}{2\sigma^2}(X_i)^2} \\ &= (\frac{1}{\sqrt{2\pi\sigma^2}})^K e^{\frac{-1}{2\sigma^2} \sum_{i=1}^{K} (u_i - \alpha v_i - \beta)^2}.\end{aligned} \tag{2}$$

Since,

$$(\widehat{\alpha}_{mle}, \widehat{\beta}_{mle}) = argmax(\ln \mathcal{L}(\alpha, \beta | X_1, ... X_K)), \tag{3}$$

$\widehat{\alpha}_{mle}, \widehat{\beta}_{mle}$ may be obtained by vanishing the partial derivatives of the likelihood function's logarithm, $(\frac{\partial \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \alpha}, \frac{\partial \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \beta})$, then resolving the resulting equations. The resulted estimators are,

$$\widehat{\alpha}_{mle} = \frac{\sum_{i=1}^{K} u_i \sum_{i=1}^{K} v_i - K \sum_{i=1}^{K} v_i u_i}{(\sum_{i=1}^{K} v_i)^2 - K \sum_{i=1}^{K} v_i^2}, \tag{4}$$

$$\widehat{\beta}_{mle} = \frac{1}{K}(\sum_{i=1}^{K} u_i - \frac{\sum_{i=1}^{K} u_i \sum_{i=1}^{K} v_i - K \sum_{i=1}^{K} v_i u_i}{(\sum_{i=1}^{K} v_i)^2 - K \sum_{i=1}^{K} v_i^2} \sum_{i=1}^{K} v_i). \tag{5}$$

If the network is homogeneous, it yields different means at different nodes for the variable delays, i.e $X_{ui} \sim \mathcal{N}(\mu_1, \sigma_1^2)$, $X_{vi} \sim \mathcal{N}(\mu_2, \sigma_2^2)$. In this case, X_i would not be a zero-mean Gaussian, but $X_i \sim \mathcal{N}(\mu_1 - \mu 2, \sigma_1^2 + \sigma_1^2)$. The likelihood function and estimators may calculated using the same method, as in [26], but would result to more complex expiration. Homogenous network has been considered herein for simplification.

IV. Multi-hop Extension

Now consider node, n_1, synchronization to another remote node, n_h, and assume the established route is $\{n_1, n_2, n_3, ..., n_h\}$. MLEs of local synchronization parameters on each hop (n_i, n_{i+1})– where $i \in \{1, ..., h-1\}$– are to be calculated as described in Section III. They will be used in the following multi-hop extension.

Let t_{n_i} denotes the time reading of node n_i's clock at instant t, and $\alpha_{n_i \to n_j}$ (respectively $\beta_{n_i \to n_j}$) denote the relative skew (respectively offset) relating time at node, n_i, to the corresponding one at node, n_j. That is, $t_{n_j} = \alpha_{n_i \to n_j} t_{n_i} + \beta_{n_i \to n_j}$. Time readings of nodes on the route can thus be related by:

$t_{n_i} = \alpha_{n_{i+1} \to n_i} t_{n_{i+1}} + \beta_{n_{i+1} \to n_i}, i \in \{1, ..., h-1\}$

By successive substitutions of $t_{n_{i+1}}$ expressions in t_{n_i} equations ($i \in \{h-2, ..., 1\}$), the following may be obtained,

$$t_{n_1} = (\prod_{i=1}^{h-1} \alpha_{n_{i+1} \to n_i}) t_{n_h} + \sum_{i=2}^{h-1} [(\prod_{j=2}^{i} \alpha_{n_j \to n_{j-1}}) \beta_{n_{i+1} \to n_i}] + \beta_{n_2 \to n_1}.$$

Consequently,

$$\alpha_{n_h \to n_1} = \prod_{i=1}^{h-1} \alpha_{n_{i+1} \to n_i}, \quad (6)$$

$$\beta_{n_h \to n_1} = \sum_{i=2}^{h-1} [(\prod_{j=2}^{i} \alpha_{n_j \to n_{j-1}}) \beta_{n_{i+1} \to n_i}] + \beta_{n_2 \to n_1}. \quad (7)$$

For the sake of simplification, $\alpha_{n_{i+1} \to n_i}$ ($i \in \{1, .., h-1\}$) is denoted in the following by α_{i+1} (the initial term α_1 is set by definition to 1), $\beta_{n_{i+1} \to n_i}$ is denoted by β_{i+1}, $\alpha_{n_h \to n_1}$ by α, and $\beta_{n_h \to n_1}$ by β. Applying these notations to Eq. 6 and Eq. 7, α and β estimators can be written as,

$$\widehat{\alpha} = \prod_{i=2}^{h} \widehat{\alpha}_i, \quad (8)$$

$$\widehat{\beta} = \sum_{i=1}^{h-1} [(\prod_{j=1}^{i} \widehat{\alpha}_j) \widehat{\beta}_{i+1}], \quad (9)$$

where $\widehat{\alpha_i}$, $\widehat{\beta i}$ on each hop, represent local MLE estimators that are calculated as described in Section III.

V. CRLB for Multi-hop Estimators

In this section, the Cramer-Rao Lower Bound (CRLB) for multi-hop estimation is provided. The joint *multi-hop* likelihood function is given by, $\mathcal{L}(\alpha, \beta | X_{i,j}, i \in \{1, ..., K\}, j \in \{2, ..., h\}) = \prod_{i=1}^{K} \prod_{j=2}^{h} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-1}{2\sigma^2}(X_{i,j})^2}$

$$= (\frac{1}{\sqrt{2\pi\sigma^2}})^{K(h-1)} e^{\frac{-1}{2\sigma^2} \sum_{i=1}^{K} \sum_{j=2}^{h} (u_{i,j} - \alpha_j v_{i,j} - \beta_j)^2}, \quad (10)$$

where $X_{i,j}$ stands for the i^{th} sample on the j thhop, which is a Normal rv.

The corresponding CRLB can be derived from the inverse of the 2×2 Fisher information vector, say I^{-1}, using the property, $Var(\widehat{\alpha}) \geq (I^{-1})_{1,1}$, $Var(\widehat{\beta}) \geq (I^{-1})_{2,2}$. I is defined as [27, p. 343].

$$I = \begin{bmatrix} -\frac{\partial^2 \ln \mathcal{L}(\alpha, \beta | X_{i,j})}{\partial \alpha^2} & -\frac{\partial^2 \ln \mathcal{L}(\alpha, \beta | X_{i,j})}{\partial \alpha \partial \beta} \\ -\frac{\partial^2 \ln \mathcal{L}(\alpha, \beta | X_{i,j})}{\partial \beta \partial \alpha} & -\frac{\partial^2 \ln \mathcal{L}(\alpha, \beta | X_{i,j})}{\partial \beta^2} \end{bmatrix}. \quad (11)$$

I^{-1} can thus be given by,

$$I^{-1} = \frac{1}{\frac{\partial^2 \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \alpha^2} \frac{\partial^2 \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \beta^2} - (\frac{\partial^2 \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \alpha \partial \beta})^2} \times \begin{bmatrix} -\frac{\partial^2 \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \beta^2} & \frac{\partial^2 \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \alpha \partial \beta} \\ \frac{\partial^2 \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \beta \partial \alpha} & -\frac{\partial^2 \ln \mathcal{L}(\alpha,\beta|X_{i,j})}{\partial \alpha^2} \end{bmatrix}. \quad (12)$$

From Eq. 8 and Eq. 9, we get,

$$\alpha_j = \frac{\alpha}{\prod_{m=2, m \neq j}^{h} \alpha_m} \quad (13)$$

$$\beta_j = \frac{\beta - \sum_{l=1, l \neq j-1}^{h-1} (\prod_{m=1}^{l} \alpha_m) \beta_{l+1}}{\prod_{m=1}^{j-1} \alpha_m} \quad (14)$$

Replacement of α_j, and β_j, respectively from Eq. 13 and Eq. 14, in Eq. 10 yields Eq. 15. The logarithm of this likelihood function is given by Eq. 16. Finally, after calculating partial derivatives of Eq. 16, Eq. 17 and Eq. 18 are obtained, representing the CRLB of the skew and offset, respectively.

VI. Numerical Analysis

To evaluate the accuracy of the proposed estimators, a simulation study has been carried out using MATLAB. A linear network of nine nodes (eight hops) has been simulated. The standardized mean square error (MSE) has been calculated for different sample sizes (K) and hops number (h), and compared to the theoretical lower bound (CRLB). Real parameters (α, β) have been repeatedly and randomly selected, as well as reception delays, constructing a set of 10^3 scenarios for each tuple (K, h). Each point of the plot is presented with an error bar of 99% confidence interval. Figures 1, 2, 3 represent α estimation MSE respectively for one, four, and eight hops. The figures shows quadratic decrease and convergence towards the CRLB as the number of signals (K) increases. The MSE does not exceed the order of 10^{-6} even for eight hops, which represents a very high accuracy. The same can be noted for β (Figures 4, 5, 6), but with moderately higher values for both MSE and CRLB. Still, the MSE does not exceed 10^{-5}.

$$\mathcal{L}(\alpha,\beta|X_{i,j}, i\in\{1,...,K\}, j\in\{2,...,h\}) = (\frac{1}{\sqrt{2\pi\sigma^2}})^{K(h-1)} e^{\frac{-1}{2\sigma^2}\sum_{i=1}^{K}\sum_{j=2}^{h}(u_{i,j}-\frac{\alpha v_{i,j}}{\prod_{m=2,m\neq j}^{h}\alpha_m}-\frac{\beta-\sum_{l=1,l\neq j-1}^{h-1}(\prod_{m=1}^{l}\alpha_m)\beta_{l+1}}{\prod_{m=1}^{j-1}\alpha_m})^2}, \tag{15}$$

$$\ln(\mathcal{L}(\alpha,\beta|X_{i,j}) = \ln((\frac{1}{\sqrt{2\pi\sigma^2}})^{K(h-1)}) - \frac{1}{2\sigma^2}\sum_{i=1}^{K}\sum_{j=2}^{h}(u_{i,j}-\frac{\alpha v_{i,j}}{\prod_{m=2,m\neq j}^{h}\alpha_m}-\frac{\beta-\sum_{l=1,l\neq j-1}^{h-1}(\prod_{m=1}^{l}\alpha_m)\beta_{l+1}}{\prod_{m=1}^{j-1}\alpha_m})^2, \tag{16}$$

$$(I^{-1})_{1,1} = \frac{\sigma^2\sum_{i=1}^{K}\sum_{j=2}^{h}\frac{1}{(\prod_{m=1}^{j-1}\alpha_m)^2}}{\sum_{i=1}^{K}\sum_{j=2}^{h}(\frac{v_{i,j}}{\prod_{m=1,m\neq j}^{h}\alpha_m})^2\sum_{i=1}^{K}\sum_{j=2}^{h}\frac{1}{(\prod_{m=1}^{j-1}\alpha_m)^2}-(\sum_{i=1}^{K}\sum_{j=2}^{h}\frac{v_{i,j}}{\prod_{m=2,m\neq j}^{h}\alpha_m\prod_{m=1}^{j-1}\alpha_m})^2}, \tag{17}$$

$$(I^{-1})_{2,2} = \frac{\sigma^2\sum_{i=1}^{K}\sum_{j=2}^{h}(\frac{v_{i,j}}{\prod_{m=2,m\neq j}^{h}\alpha_m})^2}{\sum_{i=1}^{K}\sum_{j=2}^{h}(\frac{v_{i,j}}{\prod_{m=1,m\neq j}^{h}\alpha_m})^2\sum_{i=1}^{K}\sum_{j=2}^{h}\frac{1}{(\prod_{m=1}^{j-1}\alpha_m)^2}-(\sum_{i=1}^{K}\sum_{j=2}^{h}\frac{v_{i,j}}{\prod_{m=2,m\neq j}^{h}\alpha_m\prod_{m=1}^{j-1}\alpha_m})^2}. \tag{18}$$

VII. Conclusion

Reference broadcast synchronization (RBS) used in multi-hop networks has been considered. The maximum likelihood estimator (MLE) for both skew and offset have been first calculated for single-hop environment, then extended to multi-hop networks using a proposed model. The Cramer-Raoo lower bounds (CRLB) of the joint estimators have accordingly been derived. This may represent a theoretical lower bound to any unbiased estimator. The proposed estimators have been compared by simulation to their respective CRLB, for different values of sample size (number of signals) and number of hops. The results show very low MSE and an increase of the

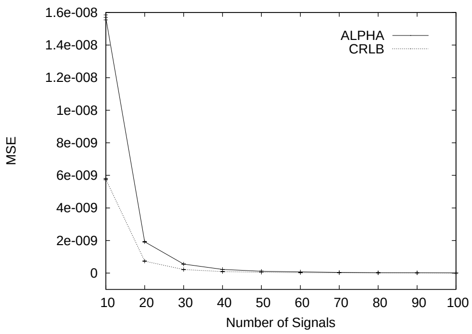

Fig. 1. MSE of one-hop α estimation and CRLB vs. number of signals

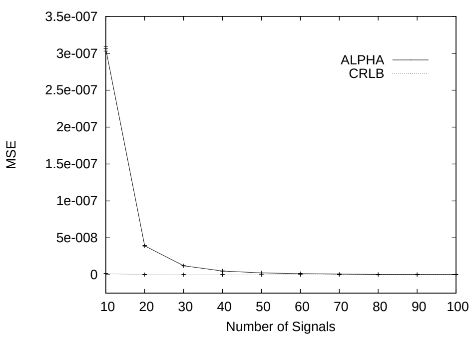

Fig. 2. MSE of four-hop α estimation and CRLB vs. number of signals

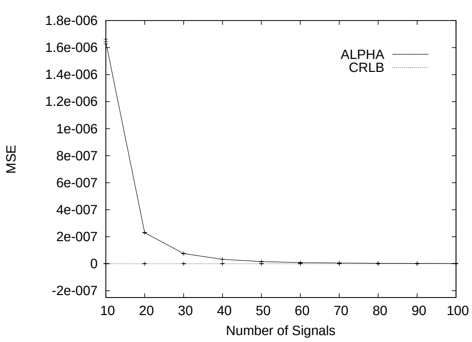

Fig. 3. MSE of eight-hop α estimation and CRLB vs. number of signals

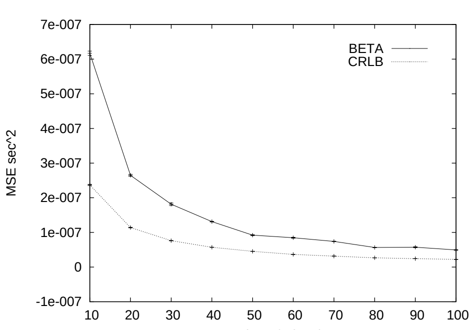

Fig. 4. MSE of one-hop β estimation and CRLB vs. number of signals

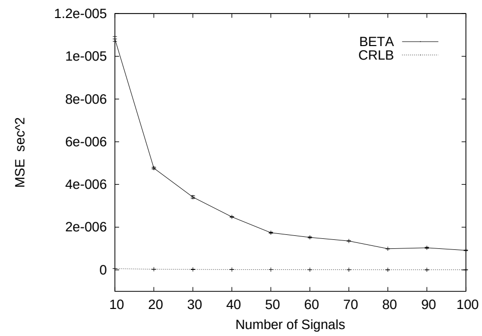

Fig. 5. MSE of four-hop β estimation and CRLB vs. number of signals

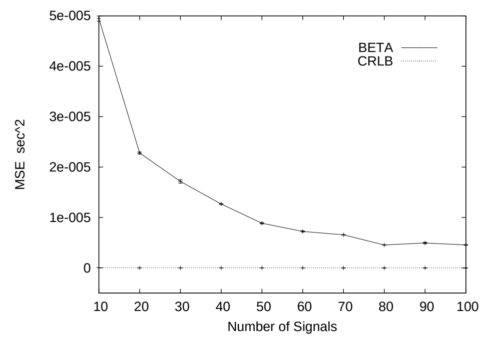

Fig. 6. MSE of eight-hop β estimation and CRLB vs. number of signals

precision with the sample size. They also demonstrate fast convergence towards the CRLB. To our knowledge, this work is the first that explores MLE for RBS extension to multi-hop networks, and derives appropriate CRLB.

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