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An Improved & Smart Clock Synchronisation Model for Emblematic IoT Applications

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Abstract

The Internet of Things (IoT) has revolutionized modern living by facilitating seamless data exchange between interconnected devices across diverse applications such as healthcare, smart cities, and industrial automation. These devices operate in dynamic and distributed environments, where accurate timekeeping is crucial for synchronizing processes, ensuring reliable communication, and maintaining data consistency. Clock synchronization plays a critical role in coordinating the activities of IoT entities, especially when processing and communication require precision. To address challenges associated with synchronization errors, this paper introduces a novel clock synchronization algorithm grounded in linear quadratic regression. By leveraging a linear model to estimate clock parameters such as skew and offset, the algorithm improves the reliability and accuracy of time synchronization in IoT networks. The effectiveness of the proposed algorithm was evaluated using key statistical metrics, including R-Square and Root Mean Square Error (RMSE). The results demonstrated the superiority of the algorithm, achieving an R-Square error value of 0.71% and an RMSE of 0.379%, outperforming traditional synchronization methods. Furthermore, the stability and robustness of the model were validated through a correlation coefficient analysis, which revealed a strong correlation of 86% between the variables. These findings underscore the algorithm's potential to significantly reduce synchronization errors, thereby enhancing the efficiency and reliability of IoT applications. By addressing a critical challenge in IoT communication, this research contributes to the advancement of time-sensitive applications and underscores the importance of innovative synchronization mechanisms in the growing IoT ecosystem.

Keywords: Clock Synchronisation, Clock Skew Internet of Things (IoT), Linear Quadratic Model, Regression, Sensors

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1. Introduction

Clock synchronisation has largely impacted technologies driven by applications in the communications and telecom sectors. However, recent development in automation, manufacturing, exploration of oil and gas, power generation and mining industries rely on precise timestamps of data.
The Internet of Things (IoT) is a groundbreaking innovation that has become a cornerstone of modern technological advancements. Its extensive capabilities and transformative impact on daily life have been widely recognized and documented in several studies [1-4]. IoT is poised to revolutionize numerous industries by bridging the gap between the physical and digital worlds, leveraging a blend of Information Technology (IT) and Operational Technology (OT) networks.
IT networks primarily provide cloud-based infrastructures that enable network connectivity, data storage, processing, and analysis. In contrast, OT networks consist of diverse connectivity technologies, protocols, and tools that facilitate the interaction of IoT endpoints, such as sensors,

actuators, and effectors, within localized networks. These networks collaboratively enable IoT to deliver robust solutions tailored to various industrial and consumer needs. Despite its potential, designing a reliable and precise IoT system remains a significant challenge [5]. The integration of advanced technologies, including artificial intelligence (AI), blockchain, and 5G, is essential to delivering high-quality services, minimizing costs, improving precision, and reducing reliance on human intervention. IoT applications depend heavily on the internet for visualization and communication, linking the physical and digital realms [6]. However, the interoperability among heterogeneous devices and resources continues to pose a barrier to seamless integration [7].

Many industrial IoT applications require precise coordination among sensors, actuators, and effectors. For time-sensitive and low-latency tasks, such as those in autonomous vehicles and smart manufacturing, sensor data must be processed in real-time. This necessitates accurate timestamps for data collected from multiple sensors. Moreover, IoT systems are expected to deliver actionable analytics derived from stored and real-time data. These analytics are meaningful only when the temporal context of events is accurately captured and interpreted. Consequently, time synchronization has emerged as a critical enabler for real-time IoT applications, especially in sectors like healthcare, manufacturing, and industrial automation.

IoT has proven particularly impactful in healthcare in developing countries like India, where it offers cost-effective and accurate solutions. A 2016 UNICEF report [6] highlighted India's high neonatal mortality risk, particularly in low-income regions. IoT-enabled solutions can alleviate this by ensuring quality care, addressing staffing shortages, and reducing costs [7]. The aging global population and rising prevalence of chronic illnesses further underscore the need for IoT-driven healthcare innovations. Distributed IoT systems, for instance, enable the collection of spatial and temporal datasets for applications such as structural health monitoring [8]. These systems require synchronized data acquisition from multiple sensors to analyze spatial constraints accurately.

To achieve effective synchronization, IoT networks must maintain a consistent and coherent understanding of temporal information. This synchronization is critical for periodic tasks such as sampling and data selection. For certain local wireless sensor network (WSN) deployments, such as industrial automation systems, tasks must be completed within specified time limits to ensure operational efficiency [9-10]. Recent advancements in time-synchronized protocols like IEEE 802.15.4e and the application of Time-Sensitive Networking (TSN) standards in 2024 and 2025 have significantly improved IoT infrastructure reliability and scalability [11-12].

The proposed paper presents a detailed analysis of time synchronization errors across various IoT modules and introduces a linear quadratic regression (LQR)-based clock synchronization algorithm to address these errors. By implementing this algorithm, the efficiency and performance of IoT applications can be significantly enhanced, reducing clock discrepancies among sensors, actuators, and effectors in real-time environments. This approach ensures robust, scalable, and secure synchronization, paving the way for advanced IoT solutions in critical applications across multiple sectors.

This paper is structured as follows: Section II covers the motivation and literature survey, while Section III highlights the importance of clock synchronization and its parameters for IoT applications. Section IV introduces an IoT-based agricultural data collection model, and Section V details the linear regression model. Sections VI-VIII provide an in-depth explanation of the proposed linear quadratic regression model for clock skew estimation, along with its validation. Section IX discusses the model's stability, and Section X concludes the research.

2. Related Work

Traditional clock synchronization techniques in IoT and Wireless Sensor Networks (WSNs) often rely on a master-slave architecture, where slave devices synchronize their clocks with a designated master device or reference time. However, a fully distributed synchronization approach has also emerged as a viable alternative, offering a common time base for all connected devices in WSNs and IoT-based applications. This section explores procedures and algorithms for achieving accurate clock synchronization, with a focus on presenting a comprehensive overview of synchronization techniques, classifying key research domains, and highlighting the state-of-the-art advancements.

In reviewing the state-of-the-art, particular attention is given to estimation-based algorithms, which form the foundation for identifying research opportunities. Table I outlines critical parameters underscoring the importance of clock synchronization, such as accuracy, scalability, and robustness. Additionally, various applications requiring WSN and IoT networks to perform tasks within stringent time constraints are surveyed and summarized in Table II. These include industrial automation, smart grids, and healthcare applications, each with unique synchronization requirements.

Notably, different IoT applications necessitate diverse notions of time, which influence the choice of methodologies and synchronization techniques. Consequently, a detailed survey is essential to provide a clear overview of the components and associated solutions tailored for specific IoT applications. Table III presents an analysis of individual components crucial for synchronization, evaluating their advantages and limitations in the context of IoT deployment.

Recent advancements in IoT synchronization, particularly those highlighted in IEEE publications from 2024 and 2025, emphasize the integration of Time-Sensitive Networking (TSN) protocols and edge-based synchronization techniques. These innovations aim to address the limitations of traditional methods by improving synchronization accuracy and reducing latency in real-time applications [49-50].

Table I: Survey on Importance of Clock Sychronisation

Parameter	Relevance	Ref.
Accuracy	Achieving a high level of synchronisation accuracy can lead to reduced energy requirements and consumption, which is especially important in wireless communication due to its broadcast nature. Clock offset and clock skew are two important parameters that have been defined to help achieve this synchronisation.	[11-13]
Scalability and bandwidth efficiency	Scalability and bandwidth efficiency is important parameter for any network, Clock synchronisation requires exchange of messages which includes overhead and consumes exchange. If clock synchronisation is efficiently, will increase bandwidth consumption.	[14-15]
Computational efficiency	Synchronized network and nodes will be better available with additional computing power.	[15]
Robustness	Robustness is an important parameter in a highly dynamic IoT infrastructure. Synchronisation will help in maintaining a high robust system.	[16]
Security	Security is a major concern especially in terms of IIoT. Secure and efficient clock synchronisation protocol protects the networks against attacks and malicious nodes.	[15]

Table II: Survey on Time-Constraint Application of WSN and IOT

Application	Description	Ref.
Industrial Automation or Industrial Wireless sensor Network	According to a survey, Industrial wireless sensor networks (IWSN) are projected to increase by 553% and reach nearly 24 million installed sensor points in the next five years. These networks utilize a variety of protocols, such as Zigbee, Wireless-HART, ISA-100.11a, Wi-Fi Low power, and Bluetooth Low Energy.	[17,18]
Low-jitter application	These applications necessitate compensation and estimating time uncertainty sources, which may arise from oscillators and communication objects.	[16]
Time Synchronized Channel Hopping (TSCH) Network	The networks are constructed using IEEE 802.15.4e protocols and have the backing of several IETF standards with support for IPv6.	[19-21]
Intelligent Transport Systems	VANETs (Vehicular Adhoc Networks) are an advancement of Mobile Adhoc Networks (MANETs).	[16, 22]
Smart Grid	IoT based Smart grid deployment depends on coherent and accurate notion of time within the networks.	[23]
Industrial Internet of Things (IIoT)	IIoT have gained interest with the development of supporting and time aware precise time stamped operations.	[24]

Table III: Surveys on Time Synchronisation for IOT Applications

Year	Component	Ref.
2004	In early 2004 a survey provided an analysis and requirement of sensors time synchronisation.	[25]
2005	A survey on various clock synchronisation for wireless sensor networks was conducted to analyze its importance and need.	[26]
2011	In 2011 clock synchronisation in WSN is analyzed in terms of signal processing. It summarizes clock relational models, estimator's parameter, exponential distributed delays, and related estimation methods with respect to signal processing.	[27]

2015	It classified clock synchronisation methods based on features classified as structural, technical, and global.	[28]
2018	Protocols to reduces the synchronisation errors in clock to enhance WSN lifetime were designed	[29-30]
2019	A consolidated review for clock synchronisation techniques applied for WSN achieving an IoT deployment.	[31]
2021	An energy efficient and practical solutions for clock synchronisation were developed and deployed	[32-33]

In WSN & IoT clock synchronisation is one of the extensively investigated challenges for real time applications. In this work, the focus is primarily on the low-cost, efficient, and low-power clock synchronisation for various networks with respect of synchronisation error. Table IV presents a detailed surveys on different clock synchronous networks.

Table IV: Clock Synchronous Networks

Network	Content	Ref.
Time-sensitive networking (TSN)	TSN is a new LAN technology for the synchronisation of operation and information. This is designed to support in-vehicle network, industrial automation, and avionic networks for Industrial IoT.	[34]
Ultra-low latency networks	The operational capabilities of an ultra-low latency network are dependent on Ethernet, which makes Time-Sensitive Networking (TSN) a cost-effective option due to its interoperability and other benefits.	[35]
Time synchronisation in vehicular ad-hoc networks	In vehicular ad hoc networks (VANETs) for automated and connected network nodes, vehicles must be synchronized for sharing information for various road safety applications related to time-critical locations and warning messages.	[36]
Packet Switched Network	In 2016, a survey on a packet-switched protocol for synchronizing devices over standardized and regular technologies and applications.	[23-37]

The design of an improved and smart clock synchronization model for emblematic IoT applications draws insights from various aspects of distributed computing and secure system operations. A foundational challenge, as highlighted by Upadhyay and Banerjee [47], lies in developing energy-efficient frameworks for time synchronization in wireless sensor networks, which are crucial for the coherent operation of IoT devices where resources are often constrained. Beyond the core synchronization mechanisms, the overall integrity and security of IoT applications are paramount. In this context, Kaur and Upadhyay [48] addressed the critical issue of application permissions and information security on smartphones, an area whose principles extend to protecting data and ensuring the reliability of operations within the broader IoT ecosystem, where accurate timestamps derived from synchronized clocks are fundamental for data integrity and event sequencing. Moreover, the increasing adoption of distributed ledger technologies, exemplified by Mishra, Singh, and Singh's [49] work on blockchain in supply chain operations, underscores the necessity for robust time management in highly distributed and potentially ambiguous environments; although not directly focused on clock synchronization algorithms, the effective functioning and consensus mechanisms of such systems inherently rely on a consistent and trustworthy temporal ordering of events, thereby emphasizing the foundational role of precise synchronization in maintaining systemic reliability and data consistency in complex IoT deployments.

Some of the other latest work done with respect to time synchronisation problems in IoT frameworks are Data Repairing Framework for ERI Data [52], Anomaly detection [53], etc.

3. Clock Model and Its Parameters

The Internet of Things (IoT) is set to revolutionize daily life by enabling seamless data exchange among interconnected devices. Achieving real-time performance for critical applications like Industrial IoT (IIoT) and Vehicular Ad hoc Networks (VANETs) necessitates clock-synchronized sensor networks that ensure data ordering and synchronous operations. Traditional solutions, such as the Network Time Protocol, are unsuitable for resource-constrained devices, prompting the development of specialized clock synchronization methods tailored for such environments [38], [39], [40]. These methods aim to enhance the accuracy and performance of IoT applications. Experimental evaluations of these protocols, conducted by the Autonomous Networks Research Group at the University of Southern California, have provided valuable insights and datasets [42].

Clock synchronization in IoT relies on understanding two critical parameters: clock offset (θ) and clock skew (α). Clock offset refers to the timing difference between two sensor clocks, influenced by factors like environmental conditions and oscillator aging. Clock skew, on the other hand, represents variations in the frequency of sensor clocks, which can arise from short-term instabilities (e.g., temperature fluctuations) and long-term instabilities (e.g., oscillator aging). These instabilities necessitate periodic synchronization to maintain system coherence. An ideal clock can be represented mathematically as:

$$C(tr) = tr \tag{1}$$

However, due to imperfections in clock oscillators, the actual clock function is defined as:

$$Ci(tr) = \varepsilon + \theta + \alpha tr \tag{2}$$

Here, ε denotes a positive random delay, θ represents the clock offset in milliseconds, and α is the clock skew. The synchronization process typically involves two phases: level discovery, where a root node organizes the network into a tree-like structure, and the synchronization phase, which employs a bi-directional message-passing scheme for time exchange. These protocols and processes are crucial for ensuring the reliability and precision of IoT networks, particularly in time-sensitive applications.

Table V: Instabilities Affecting Clock Parameters

Type of Instability	Description	Examples
Short-term	Caused by environmental factors like temperature variations and supply voltage fluctuations.	Temperature, voltage fluctuation.
Long-term	This results from gradual factors such as oscillator aging.	Aging of crystal oscillators.

Table VI: Clock Synchronization Phases

Phase	Description	Methodology
Level Discovery	Designates one node as the root, forming a hierarchical structure with child nodes.	Tree-like structure formation.
Synchronization	Exchanges timing information between parent and child nodes using bi-directional message passing.	Bi-directional message scheme.

Table VII: Clock Skew Calculation

Parameter	Formula	Explanation
Clock Skew (CS)	$\alpha_{\_A,B\_}(t) = \frac{d\theta_{\_A,B\_}(t)}{dt}$ (3)	Derivative of clock offset between two nodes A and B at time tt.
Alternative Formula	$\alpha_{\_A,B\_}(t) = \frac{\theta_{\_A,B\_}(t+T(t)) - \theta_{\_A,B\_}(t)}{T_{\_}(t)}$ (4)	Utilizes sampling interval T(t)T(t) for clock skew computation.

The calculation of clock skew requires the sampling interval , as described in Equation (4). Initially, the clock offset is determined using a bi-directional message passing approach [42]. However, clock skew is subject to dynamic influences such as variations in battery levels and sensor temperature, making it unsuitable to treat as a fixed random variable. As a result, conventional methods like Maximum Likelihood Estimation (MLE) are inadequate for accurately predicting clock skew. To address this, a linear-quadratic regression model is utilized, providing a more effective method for estimating the optimal value of clock skew.

The Table V, Table VI & Table VII summarize the key information and processes for clock synchronization in IoT and WSN applications

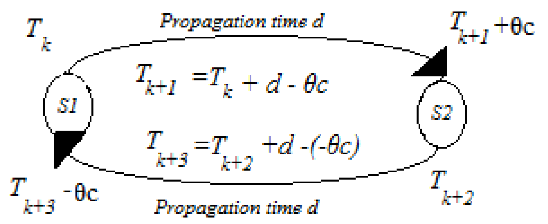

Figure 1. Bi-directional Message Exchange Scheme with Propagation Time and Clock Offset between S1 and S2.

Where θc The time offset between node S1 and node S2 is represented by t, and d is the propagation time.

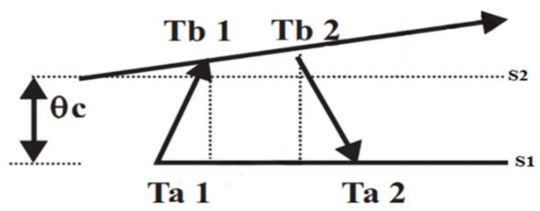

Figure 2. Bi-directional message passing scheme

Figure 1 illustrates the Bi-Directional Message Passing scheme, and Figure 2 illustrates the bi-directional message passing scheme, where θc represents the clock offset between nodes S1 and S2.

4. System Model

While existing methods for clock synchronization, such as traditional regression techniques and heuristic-based approaches, provide reasonable accuracy, they often struggle with scalability and adaptability to dynamic IoT environments. These limitations, highlighted in the Related Work section, underscore the need for a robust model capable of addressing these gaps. To bridge this gap, the proposed Linear Quadratic Regression model offers an innovative approach to enhance synchronization accuracy and reliability in resource-constrained IoT systems.

This study presents a wireless sensor network (WSN) designed for agricultural irrigation control to improve clock synchronization research. The system integrates various sensors and a Raspberry Pi to collect environmental and timing data, while MATLAB simulations analyze clock offset and skew. Bi-directional communication among nodes ensures efficient data exchange and synchronization.

Details of the system model of the Irrigation Management System deployed for Clock Synchronization Research is:

System Components

- Data Collection Setup:
    - Data includes timing information from network nodes and timestamp data traces from Maulik Desai's experiments [43].
    - Timing data is simulated in MATLAB for analysis.
- Irrigation Control System Hardware:
    - Microcontroller: Raspberry Pi.
    - Sensors:
        - N-P-K sensor.
        - Soil monitoring sensor.
        - pH sensor.
        - Moisture sensor.
        - Temperature sensor.
    - Node Communication: Nodes exchange timing messages and sensor data for synchronization.

Process Flow

- Data Collection:
    - Sensors monitor environmental conditions and transmit the data to the central control system.
    - Timing data is collected as part of bi-directional communication between nodes.
- Timing Analysis:
    - Timing information is used to estimate clock parameters like offset and skew.
    - MATLAB is employed to simulate the dataset and analyze clock synchronization metrics.

Communication Models

- Wireless Sensor Network (WSN):
    - Nodes (S1, S2, S3) form a network for agricultural irrigation management.
    - Timing messages and sensor data are exchanged wirelessly.
- Bi-Directional Communication:
    - Nodes synchronize through message exchanges to estimate clock offset and skew.
    - Illustrated in Fig. 4 as a bi-directional communication model among nodes S1, S2, and S3.

(a) Components Employed in an Irrigation Management System.

(b) Collection of Timing Data by an Irrigation Management System

Figure 3. Wireless Sensor Network Configuration for Collecting Clock Offset in an Agriculture Irrigation Control System.

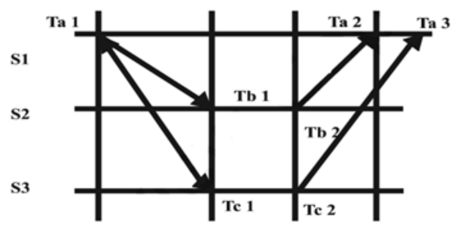

Figure 4. Bi-Directional Communication Model among Multiple Nodes S1, S2, and S3.

5. Linear Quadratic Regression Model

The linear-quadratic regression model is based on the assumption that if sample values are temporally correlated, past observations can be leveraged to predict current and future values. The proposed model approximates the clock skew sample as a linear combination of its previous values. It incorporates a linear term, an intercept, square terms, and an interaction to form the quadratic model. The estimation coefficient is determined by minimising the discrepancy between the actual skew value and the estimated skew value. A scatterplot is used to analyse the relationship between variables, demonstrating a linear trend in the clock skew dataset. Linear estimation relies on historical values of $\Delta\widehat{\alpha_{\_A,B\_(t)}}$ to predict its current value, where $\Delta\widehat{\alpha_{\_A,B\_(t)}}$ represents the estimated clock skew and $e_{\_t}$ denotes the error between the predicted $\Delta\widehat{\alpha_{\_A,B\_(t)}}$ and actual skew values. These relationships are mathematically represented in equations (5) and (6).

$$\Delta\widehat{\alpha_{\_A,B\_(t)}} = a_{\ 1\_}\Delta\alpha_{\_A,B\_(t-1)} + \cdots + a_{\_k\_}\Delta\alpha_{\_A,B\_(t-k)} = \sum_{i=1}^{k} a_{\_i}\Delta\alpha_{\_A,B\_(t-i)} \quad (5)$$

$$e_{\_t}=\Delta\alpha_{\_A,B(t)}-\Delta\widehat{\alpha_{\_A,B\_(t)}}=\Delta\alpha_{\_A,B\_(t)}-\sum_{i=1}^{k} a_{\_i}\Delta\alpha_{\_A,B\_(t-i)} \quad (6)$$

Within this context, the coefficient for estimating skew is denoted by $a_{\_i}$, and the order of estimation is represented by k. Simulation parameters for the proposed linear prediction algorithm can be found in Table VIII.

Table VIII: Parameters for Clock Skew Estimation Development

Parameters	Value
Estimation Term	Quadratic
Estimation Model Type	Linear Regression
Estimation Preset	Linear Type

The primary aim of the algorithm proposed is to create a system based on IoT that can synchronize sensors and other devices with high precision and dependability. The flowchart outlining the proposed model can be observed in Figure 5.

6. Clock Skew Estimation Model Based on Linear Quadratic Regression

The linear quadratic regression model is a statistical approach designed to model the relationship between a dependent variable, and one or more independent variables, denoted as and . The equation represents this relationship:

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + \ldots + \beta kxk + \varepsilon \quad (7)$$

Here is the intercept, which is the coefficient of the independent variables and represents the error term. For simple linear regression with one independent variable, the equation is expressed as:

$$y_{\_i} = (\beta_{\_1} * x_{\_i}) + \beta_{\_0} + \varepsilon_{\_i} \text{ for } i = 1, 2, \ldots, n \quad (8)$$

For a dataset of observations, the linear relationship is extended to include matrices in table IX:

Table IX: Relationship Matrices Representation

Term	Matrix Representation	Explanation
Linear Relationship (9)	$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{\_1} \\ 1 & x_{\_2} \\ \vdots & \vdots \\ 1 & x_{\_n} \end{bmatrix} \begin{bmatrix} 1 & z_1 \\ 1 & z_2 \\ \vdots & \vdots \\ 1 & z_n \end{bmatrix} \begin{bmatrix} \beta_{\_0} \\ \beta_{\_1} \end{bmatrix}$	General representation of the multiple linear regression model using matrices.
Independent Variable (X) **(10)**	$\begin{bmatrix} 1 & x_{\_1} \\ 1 & x_{\_2} \\ \vdots & \vdots \\ 1 & x_{\_n} \end{bmatrix}$	Represents the independent variable values for each observation.
Dependent Variable (Y) **(10)**	$\begin{bmatrix} y_{\_1} \\ y_{\_2} \\ \vdots \\ y_{\_n} \end{bmatrix}$	Represents the dependent variable values for each observation.
Second Independent Variable (Z) **(10)**	$\begin{bmatrix} 1 & z_{\_1} \\ 1 & z_{\_2} \\ \vdots & \vdots \\ 1 & z_{\_n} \end{bmatrix}$	Represents an additional independent variable for the regression model.
Coefficients (B) **(10)**	$\begin{bmatrix} \beta_{\_0} \\ \beta_{\_1} \end{bmatrix}$	Contains the intercept (β0) and slope (β1) values, which define the regression equation.

In the context of regression analysis, x_i and y_i represent the i-th observations of the independent (predictor) and dependent (response) variables, respectively. These variables are essential for understanding the relationship between the input and output of a given dataset. The goal of regression analysis is to model how changes in the independent variables (x_i) affect the dependent variable (y_i) by estimating the parameters of the regression equation. The linear relationship is defined by the coefficients β_0 (the intercept) and β_1 (the slope for the independent variable), which are determined through statistical techniques such as least squares estimation. These coefficients describe the extent and nature of the relationship, indicating how the dependent variable changes in response to variations in the independent variable.

The first equation refers to a multiple linear regression model where k independent variables influence the dependent variable y. This generalized form extends the simple linear regression model by incorporating additional predictors, each contributing to the variation in y. The coefficients $\beta_1,\beta_2,\ldots,\beta_k$ quantify the individual effect of each predictor variable, while β_0 represents the baseline value of y when all predictors are zero. On the other hand, the second equation is specific to a simple linear regression model, where only one independent variable x_i is used to predict y_i. This simpler model provides a clearer understanding of the direct relationship between a single predictor and the outcome, making it suitable for scenarios where the influence of one variable is isolated. Both models serve as fundamental tools for analyzing data and uncovering relationships between variables in various fields.

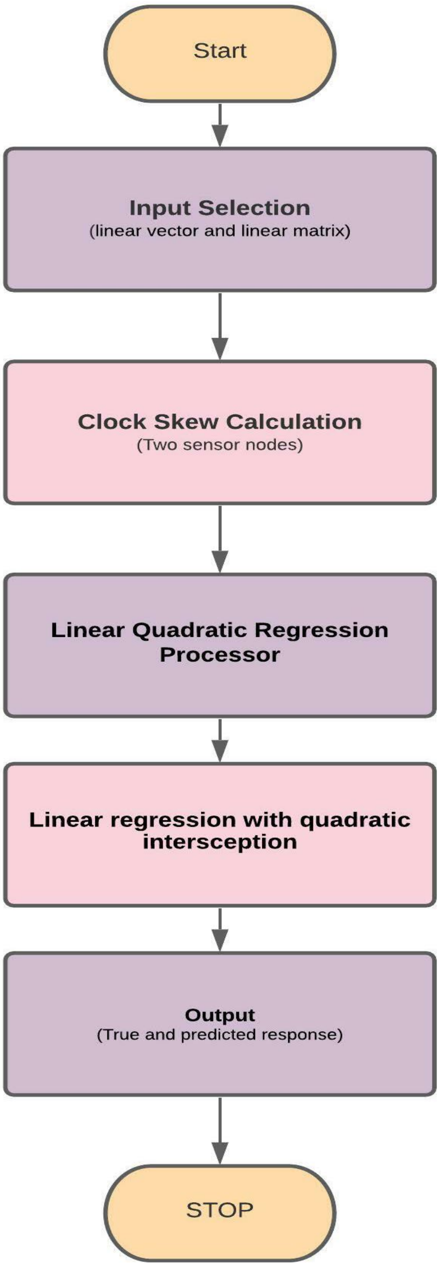

Figure 5. Proposed clock skew estimator using linear quadratic regression can be visually represented through a flowchart

The linear relation for observed 'n' values is shown in equation 9:

$$[Y]= [Z] [B] [X] \tag{11}$$

Steps for Clock Skew Estimation

1. *Collect the timestamps from two sensor nodes, A and B.*
2. *Calculate the time difference between the timestamps of A and B, i.e., Δ_t = timestamp_A - timestamp_B.*
3. *Calculate the clock skew between A and B using the formula: $\Delta\alpha = \Delta t - \Delta\beta$, where $\Delta\beta$ is the clock offset between A and B.*
4. *Collect a dataset of clock skews and corresponding timestamps from A and B.*
5. *Split the dataset into training and testing sets.*
6. *Apply linear quadratic regression to the training set to create a model for clock skew estimation.*
7. *Evaluate the model using the testing set by calculating the errors for RMSE, MAE, MSE, and R^2.*
8. *Use the trained model to estimate the clock skew between A and B by providing the timestamp difference Δt as input to the model.*
9. *Verify the accuracy of the estimated clock skew by comparing it with the actual clock skew using the testing set.*
10. *Refine the model by adjusting the model parameters or collecting more data if necessary.*

Algorithm for Clock Skew Estimation

1. Calculate the differences in clock skew between nodes A and B.
2. Use the differences and corresponding timestamps as input for the regression processor.
3. Apply the regression model with linear and quadratic terms to estimate .
4. Visualize results:

Figure 6. Analysis of performance for the Linear Quadratic Regression Model for Synchronisation Error in Node A and B.

Figure 6 represents the analysis of synchronization error using the linear quadratic regression model.

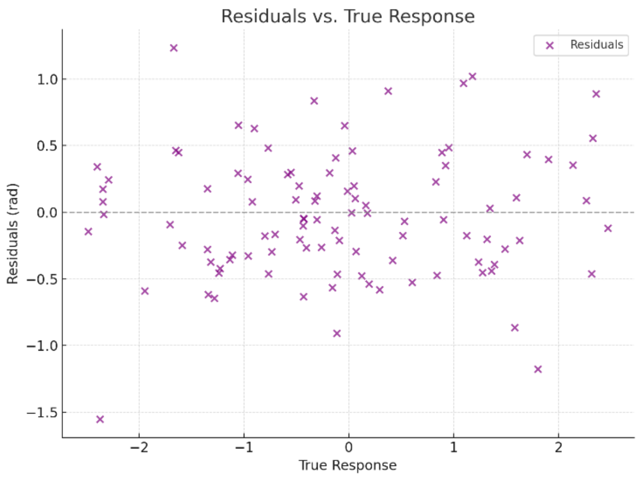

Figure 7. Actual and estimated outcomes

Figure 7 represents the Comparison of actual vs. estimated values and figure 8 presents the residual plot for the regression model.

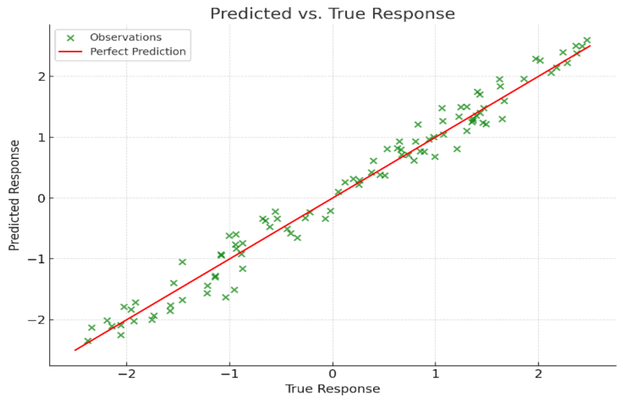

Figure 8. Plot of residuals for a linear quadratic regression mode.

This approach provides a robust framework for clock skew estimation, enabling precise synchronization in IoT and sensor networks.

7. Model Validation

Model validation is an essential step in assessing the performance of any model. Evaluating the goodness of fit is a key part of the validation process.

- Residual plots serve as a fundamental statistical tool for evaluating model performance.
- For linear regression models, residual plots are critical to ensure:
  - The regression function is well-defined.
  - The distribution of errors is consistent and independent.

The residual plot for the proposed linear regression estimator is shown in Figure 8 to validate its accuracy and reliability.

8. Performance Evaluation

Figure 9 presents the results of evaluating the effectiveness of the linear-quadratic regression model for estimating clock skew in this study. To measure the accuracy of the model, we used commonly used metrics such as R-square, mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE).

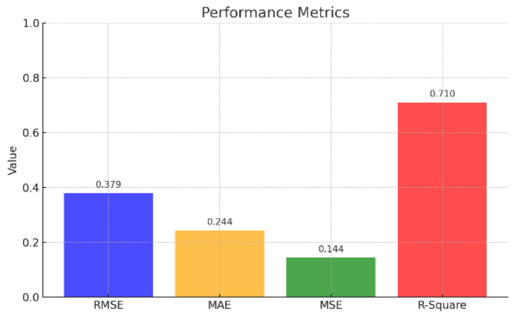

Figure 9. The goodness of fit based on RMSE, R-Square, MSE and MAE for the proposed model

The results achieved with the proposed model demonstrated its strong performance and reliability. A significant reduction in the Root Mean Square Error (RMSE) to 0.379 highlights the model's accuracy in estimating clock skew. This low RMSE value indicates that the predicted clock skew values closely align with the actual values, reducing synchronization errors significantly. Additionally, the R-square value, which measures the goodness of fit of the model, was calculated to be 0.71. This value, ranging from 0 to 1, confirms that the model effectively captures the variance in the dataset, making it a robust solution for clock skew estimation.

Further analysis of the proposed model emphasized its efficiency in terms of estimation speed and training time. These metrics are critical for real-time applications where quick and accurate estimations are required to maintain synchronization in IoT-based systems. Table VII presents a detailed breakdown of the model's performance, showcasing its ability to deliver results with minimal computational overhead. This efficiency is particularly beneficial for IoT and WSN devices, which often operate with limited processing power and energy resources.

The proposed model's combination of high accuracy and efficiency positions it as an optimal solution for addressing clock skew challenges in IoT applications. Its performance not only meets the technical requirements for synchronization but also ensures scalability and adaptability in various real-world scenarios. These results underline the practical applicability of the model and its potential to enhance the performance of IoT-based systems through precise and reliable clock synchronization.

Table X: Performance Metrics for Proposed Model: Estimation Speed and Training Time

Time taken for Training	Prediction Speed
1.725 secs	~1800 obs/sec

A detailed comparative analysis was conducted to evaluate the performance of the proposed linear-quadratic regression (LQR) model against existing models. The models used for comparison included Gaussian Process Regression (GPR) [45], Linear Regression (L.R.) [44], and Nonlinear Gaussian Regression (NGR) [46]. The analysis focused on estimating clock skew using timestamps from the same dataset, ensuring a consistent basis for comparison across all models.

The results, illustrated in Figure 10, clearly indicate the superior performance of the LQR model over the other approaches. Among the models compared, the LQR model demonstrated higher precision and reliability in estimating clock skew, with a significant reduction in error rates. This underscores the effectiveness of the proposed model in addressing the challenges associated with clock synchronization in IoT and WSN applications.

One of the key findings of the study was the average RMSE value of 0.35 achieved by the LQR model, which reflects its high accuracy. This value highlights the model's capability to provide reliable estimates, making it a robust solution for clock skew estimation. The results validate the suitability of the proposed LQR model for practical applications where accurate time synchronization is critical, such as IoT-based systems.

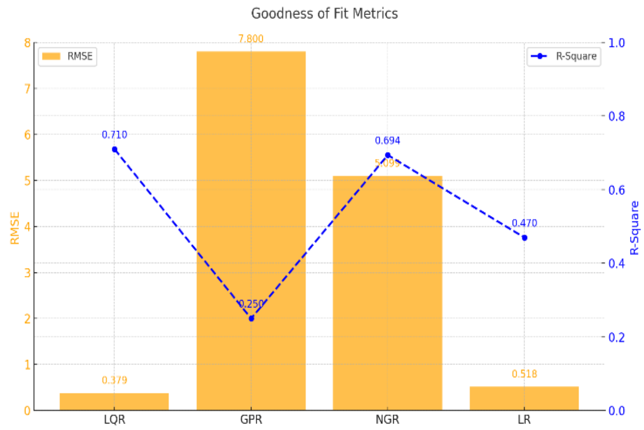

Figure 10. Comparing the Goodness of Fit of Linear Quadratic Regression (LQR) with Gaussian Process Regression (GPR), Nonlinear Gaussian Regression (NGR) AND LINEAR Regression (L.R.) Models.

9. Model Stability Evaluation

Linear Quadratic Regression models determine the best-fit parabolic equation for a given dataset. When applied to clock skew estimation, the linear quadratic regression model is represented by equation [7]. The reliability of the proposed approach can be evaluated by computing the correlation coefficient (Cr) and interpreting it based on the standards illustrated in Figure 11.

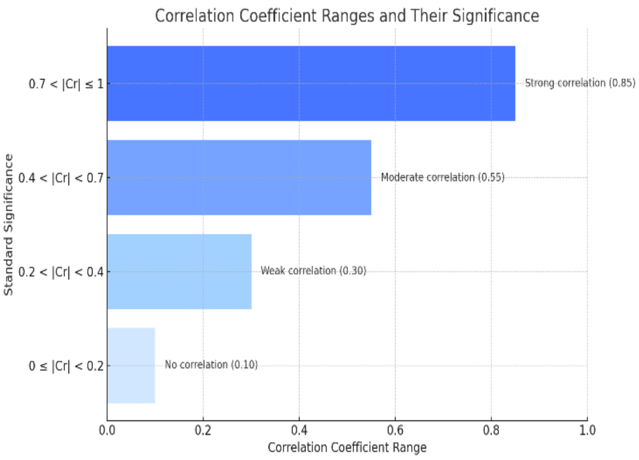

Figure 11. Standards for Correlation Coefficient

Formula for calculating the mean for the linear quadratic regression model defined by (7) is shown in (12).

$$\text{mean: } \bar{x}=n\sum xi,\ \bar{y}=n\sum yi,\ \bar{z}=n\sum zi \tag{12}$$

The intercept term (β0 and coefficients (β1,β2) for the model are defined as (13), (14), &(15):

$$\beta 0=\bar{y}-\beta 1\bar{x}+\beta 2\bar{z}+e \tag{13}$$

$$\beta_1 = \frac{\tau_{xy}\tau-\tau_{zy}\tau_{xz}}{\tau_{xx}\tau_{zz}-(\tau_{xz})^2} \tag{14}$$

$$\beta_2 = \frac{\tau_{zy}\tau_{xx}-\tau_{xy}\tau_{xz}}{\tau_{xx}\tau_{zz}-(\tau_{xz})^2} \tag{15}$$

Where, the value for function τ is defined using the correlation coefficient C_r as shown in (16).

$$C_r = \frac{\sqrt{1-\sum(yi-(\beta_0+\beta_1 x_i+\beta_2 z_i+e)}}{\sum(y_i-\bar{y})2} \tag{16}$$

Where the components of τ are represented in Figure 12.

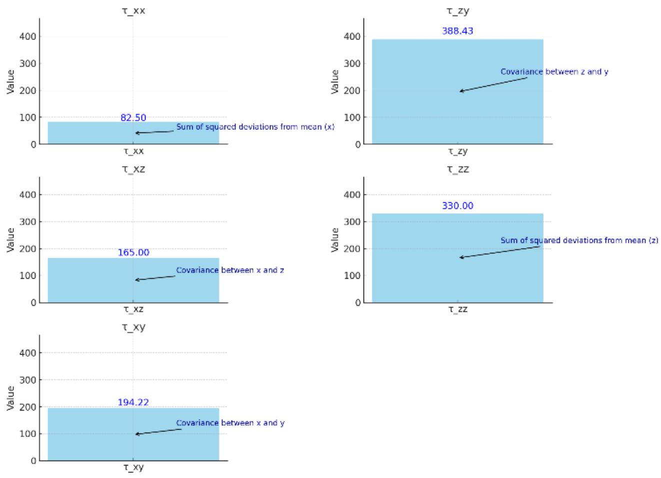

Figure 12. Detailed Representation of Components of τ

The stability of the proposed linear quadratic regression model was assessed using equation (16), resulting in a correlation coefficient of Cr = 0.86. This high correlation reflects a strong relationship between the actual and predicted clock skew values, confirming the model's reliability. Therefore, the proposed approach effectively addresses the challenge of clock synchronisation in WSN devices for IoT applications.

10. Conclusion

IoT applications are growing rapidly, posing challenges in developing accurate and dependable models. Clock synchronization for sensors and WSNs is critical for enhancing system performance.

- The proposed framework leverages a clock skew estimator using a linear-quadratic regression model to synchronize time and resynchronization intervals.
- The model demonstrates superior performance, achieving a clock skew error rate of just 0.35%, surpassing traditional linear regression models.
- Stability analysis reveals a strong correlation coefficient of 86%, affirming the model's reliability.

This framework is suitable for IoT applications requiring precise time synchronization, such as time-division scheduling, low-power communication, and coherent temporal coordination.

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