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Chapter 1
Introduction

"Time is the unseen force that intricately connects the elements of science, technology, and communication."

1.1 Precise Timekeeping

Accurate timekeeping plays a v ital role in our everyday lives, influencing everything from the synchronization of global navigation satellite systems (GNSS) and telecommunication networks to the fast-paced world of high-frequency trading [1]. It also underpins astronomical observations, large-scale scientific experiments, and even the daily coordination of transportation systems [2]. In essence, the ability to keep precise time is fundamental to the functioning of modern society. Without synchronized clocks and reference timescales, the complex networks on which humanity depends would lose their coherence, leading to inefficiencies, vulnerabilities, and in some cases, catastrophic failures [3].

The significance of timekeeping can be better understood by recognizing that modern civilization has become increasingly dependent on interlinked systems where events, data, and operations must occur in harmony [4]. From global financial transactions that must be validated within microseconds, to satellites navigating spacecraft across millions of kilometres, the requirement for precise temporal reference is ubiquitous [5]. Even the most ordinary aspects of daily life, such as using a smartphone for communication or accessing online services, rely on infrastructures that are fundamentally synchronized by accurate time signals. Timekeeping has moved from being a tool of convenience in earlier centuries to becoming an indispensable infrastructure of national and global importance [6].

The importance of time has been acknowledged throughout human history. Early civilizations developed rudimentary methods of measuring time, such as sundials, water clocks, and mechanical devices, primarily for regulating social activities, religious ceremonies, and agricultural practices [7]. With the scientific revolution and the development of mechanical pendulum clocks in the seventeenth century, the measurement of time began to acquire a new degree of accuracy. This marked the beginning of timekeeping as a scientific pursuit rather than a cultural necessity. The invention of the marine chronometer in the eighteenth-century revolutionized navigation by allowing sailors to determine longitude at sea. This development not only advanced exploration but also contributed to economic and military supremacy for nations that mastered the art of precise timekeeping. Later, in the twentieth century, quartz oscillators and, subsequently, atomic clocks enabled unprecedented accuracies. These technological advancements laid the foundation for the highly synchronized world we live in today. With atomic standards, it became possible to define the second as a physical constant, detached from astronomical observations, thereby giving timekeeping an objective and reproducible character [8].

1.2 Modern Applications of Accurate Timekeeping

In the contemporary era, accurate timekeeping is essential in multiple domains:

1.2.1 Global Navigation Satellite Systems (GNSS)

Rely on nanosecond-level synchronization of onboard atomic clocks with ground-based reference stations. Without this synchronization, positioning errors would accumulate, rendering navigation unreliable [9]. Every application that depends on GNSS, from personal GPS devices to aviation and maritime navigation, hinges on the accuracy of these synchronized signals.

1.2.2 Telecommunication Networks

Require precise timing for bandwidth allocation, signal multiplexing, and data transfer. Mobile networks, for instance, depend on synchronized base stations to prevent interference and to ensure seamless handovers between towers [10]. The explosive growth of data-driven communication, including 5G and beyond, has only amplified the importance of synchronized timing.

1.2.3 High-Frequency Financial Trading

Demands synchronization to the microsecond or even nanosecond level. Regulatory frameworks in many countries mandate precise time-stamping of financial transactions to prevent fraud, resolve disputes, and maintain transparency [11]. Even a millisecond discrepancy can result in significant financial losses or advantages.

1.2.4 Astronomical Observations and Scientific Research

Observatories across different geographical locations often operate collaboratively, requiring precise synchronization for interferometry and data integration [12]. Particle accelerators, gravitational wave observatories, and radio telescopes are just a few examples of scientific facilities where the accuracy of time measurements directly affects the integrity of experimental results.

1.2.5 Critical Infrastructure

Power grids, air traffic control, and weather forecasting systems also rely heavily on accurate time synchronization. In power distribution, synchronized measurement enables real-time monitoring of demand and fault detection [13]. In meteorology, data from distributed sensors must be time-stamped and correlated to construct accurate models for weather prediction and disaster management [14]. These applications illustrate that timekeeping today is a critical infrastructure underpinning modern technological, economic, and social systems.

1.2.6 National and Global Importance

Accurate time synchronization has moved beyond being a technical necessity, it is now a matter of strategic importance for national security and economic stability. Nations rely on their Primary Reference Time Scale (PRTS), which is often maintained by national metrology institutes using ensembles of atomic clocks [15]. This national timescale not only synchronizes domestic networks but also must remain consistent with international references such as Coordinated Universal Time (UTC) [16]. Discrepancies between national timescales and UTC can have wide-ranging consequences, from failed financial transactions to compromised satellite operations [17]. In a globalized world, where cross-border communication, trade, and cooperation are the norm, synchronization at an international level is crucial. For example, seamless operation of aviation systems, international banking, and global scientific collaborations depends on maintaining an agreed-upon reference time. Any failure in synchronization could create disruptions with both local and global repercussions.

1.2.7 Challenges and Risks

Despite its importance, accurate timekeeping faces challenges that are both technical and geopolitical. Technically, ensuring synchronization to the nanosecond or picosecond level across distributed systems is a formidable task, requiring robust infrastructure and redundancy [18]. Signal delays, atmospheric disturbances, and equipment limitations are among the factors that can degrade synchronization accuracy. From a security perspective, timekeeping systems are vulnerable to attacks such as spoofing and jamming [19]. Since many national infrastructures depend on GNSS signals for timing, deliberate interference or manipulation could cause large-scale disruption. For instance, desynchronization of financial networks or power grids could lead to economic losses and even endanger lives [20]. This has prompted growing interest in developing resilient timing sources, such as terrestrial backups, optical clock networks, and quantum-enhanced synchronization systems [21].

1.3 Background

1.3.1 The Role of Timekeeping in Emerging Technologies

Looking to the future, the importance of timekeeping is expected to increase further with the advancement of emerging technologies. The expansion of the Internet of Things (IoT), autonomous vehicles, and machine-to-machine communication will all require ultra-precise synchronization to ensure safety and reliability [22]. Quantum communication and computing, both of which rely on entanglement and coherence, will demand new levels of timing precision. Similarly, distributed ledger technologies, including block-chain, require accurate time stamping to validate transactions securely and prevent double-spending attacks [23]. Artificial intelligence and big data analytics also benefit from precise timekeeping. When massive datasets are collected from distributed sources, accurate time-stamping ensures integrity, sequence, and traceability [24]. This is particularly vital in healthcare, smart cities, and defense applications, where misaligned data could lead to faulty decisions. An accurate time synchronization and stamping is essential for the overall growth and security of the country.

1.3.2 Strategic Sectors

Precise time measurement and synchronization are indispensable to the functioning of strategic sectors such as space, defense, aeronautics, and astronomical observatories. These domains not only represent the forefront of technological advancement but also constitute critical components of national security, global competitiveness, and scientific discovery. Any disruption or inaccuracy in timing within these sectors can have consequences of unprecedented scale, ranging from economic losses to threats to national sovereignty. For this reason, all strategic sectors are synchronized to the PRTS maintained by national metrology institutes, which in turn is coordinated with international time standards such as UTC. The strategic sectors of space, defense, aeronautics, and astronomy collectively demonstrate the indispensable role of accurate timekeeping in safeguarding national interests, advancing scientific frontiers, and ensuring operational reliability. Their heavy dependence on synchronization to the PRTS underscores the necessity of investing in resilient, redundant, and secure timekeeping infrastructures. These sectors continue to evolve and adopt emerging technologies such as quantum communication, autonomous systems, and deep-space exploration, the demand for ultra-precise and resilient time synchronization will only intensify.

1.3.3 Navigation

Navigation systems critically depend on time synchronization of extremely high precision, often at the level of nanoseconds. Global Navigation Satellite Systems (GNSS), such as GPS, GLONASS, Galileo, and NavIC, operate by transmitting signals from satellites equipped with atomic clocks to receivers on Earth. The receiver calculates its position by measuring the time taken for these signals to arrive from multiple satellites. Even a timing error of a few nanoseconds can result in location inaccuracies of several meters, which may prove unacceptable for aviation, maritime, military, or autonomous vehicle applications. Thus, precise synchronization between onboard satellite clocks and ground-based receivers and transmitters is essential for determining exact position, velocity, and time (PVT) solutions. Reliable timekeeping ensures not only safe navigation and transportation but also supports critical infrastructure services, financial networks, and disaster response systems that depend on accurate geolocation.

1.3.4 International Trade

Accurate national time synchronization with respect to other countries is vital for ensuring the smooth functioning of international trade and financial markets. Global trade today is heavily dependent on electronic transactions, stock exchanges, cross-border banking systems, and international logistics, all of which require precise time-stamping of events. Even microsecond-level discrepancies in transaction records can lead to disputes, financial losses, or exploitation through fraud. High-frequency trading platforms, *e.g.*, rely on globally synchronized clocks to ensure fairness and prevent manipulation Similarly, supply chain management systems that track shipments, customs operations, and cargo handling across different time zones require uniform and accurate time references. Synchronization with Coordinated Universal Time (UTC) ensures that a nation's trade systems align seamlessly with global partners. Without such precision, mismatches could disrupt international contracts, compromise legal accountability, and erode trust in economic exchanges, ultimately hindering growth and competitiveness in the global marketplace.

1.3.5 National Security, Electronic Transactions and Cybercrimes

Accurate time synchronization is critical for national security, effective management of electronic transactions, and the prevention of cybercrimes. In the context of security, real-time monitoring of events such as civil unrest, terrorist attacks, or natural disasters requires precise coordination among multiple agencies and alarm systems. Accurate timestamps allow law enforcement, emergency responders, and military units to act swiftly and in a coordinated manner, minimizing response times and potential damage. In the financial sector, every electronic transaction—whether banking transfers, stock trades, or payment processing—must be accurately time-stamped to prevent fraud, enable auditing, and maintain accountability. Even minor discrepancies can lead to disputes or exploitation. Cybersecurity further depends on uniform synchronization across all networked devices, ensuring coherent system logs, intrusion detection, and reliable event correlation. Maintaining alignment with the national timescale provides a consistent reference that strengthens the resilience of critical infrastructure and supports secure, trustworthy digital ecosystems.

1.3.6 Weather Prediction and Disaster Management

Accurate time synchronization is indispensable for weather prediction and disaster management, where the timely collection, analysis, and dissemination of data can save lives and property. Meteorological monitoring systems, satellites, radar stations, and sensor networks must operate in precise temporal coordination to map and track dynamic phenomena such as cyclones, floods, tsunamis, and severe storms. Even minor discrepancies in timing can lead to errors in forecasting the path, intensity, or evolution of these natural disasters, reducing the effectiveness of preparedness measures. Beyond prediction, synchronized timing ensures that early warning systems, civil alert networks, traffic management, and public health notifications function seamlessly. For instance, coordinated alerts sent across mobile networks, emergency broadcast systems, and traffic control centers must be delivered simultaneously to maximize public awareness and enable timely evacuation or mitigation actions. By ensuring consistent timing across these devices and systems, authorities can enhance responsiveness, optimize resource deployment, and improve overall disaster resilience.

1.3.7 Power Grid Application

Accurate time synchronization is crucial for the efficient operation and management of modern power grids. By ensuring that all components—from generation units to substations and distribution networks—operate on a common timescale, operators can monitor system performance in real time and respond promptly to fluctuations in demand or unexpected faults. Synchronized timing enables precise measurement of electrical parameters such as voltage, current, and frequency across the grid, which is essential for detecting anomalies, preventing cascading failures, and maintaining system stability. The time-aligned data allows for optimal power flow management, enabling electricity to be rerouted dynamically according to demand, reducing losses, and improving overall energy efficiency. Advanced applications, including smart grids, renewable energy integration, and wide-area monitoring systems, rely heavily on nanosecond-level synchronization to coordinate distributed energy resources. Synchronized grids substantially contribute to national energy security and operational resilience by reducing downtime, enhancing reliability, and minimizing delays in fault detection and control actions.

1.4 National timescales and their significance

1.4.1 Defining Second

In the 13th CGPM conference in the year 1967 the “time” was defined in the SI unit as “One second is the time required for 9 192 631 770 oscillations between doubly splitted hyperfine ground states of Cesium atoms (^{133}Cs)”. After the invention of the laser cooling technology for the atoms, several dominant systematic effects were further reduced. In the year 1997, an amendment was introduced to the SI definition of second as "One second is the time required for 9 192 631 770 oscillations between doubly splitted hyperfine ground states of ^{133}Cs atoms *at 0 K temperature*", which is possible to achieve in an atomic fountain [25].

1.4.2 International Atomic Time

BIPM with the support of the timing community maintains the international time scales, *i.e.*, International Atomic Time (TAI) and Coordinated Universal Time (UTC) [26]. TAI is an integrated time scale built by accumulation of seconds. It is the basis for the realization of UTC and is used for all applications. UTC is derived from TAI by the application of an integral number of seconds that compensate for the irregular rate of rotation of the Earth. The reliability of TAI is ensured by about 350 industrial clocks operated in national laboratories, mainly cesium atomic standards and active auto-tuned hydrogen masers [27]. The frequency uncertainty of TAI is improved by comparing its frequency with that of primary frequency standard (PFS) and by applying frequency corrections if necessary. Fig. 1.1 shows the relation between different timescales that also includes fifteen PFS, out of which 11 cesium fountains developed and maintained in some of the national laboratories, have been contributing frequency measurements since 2007[28].

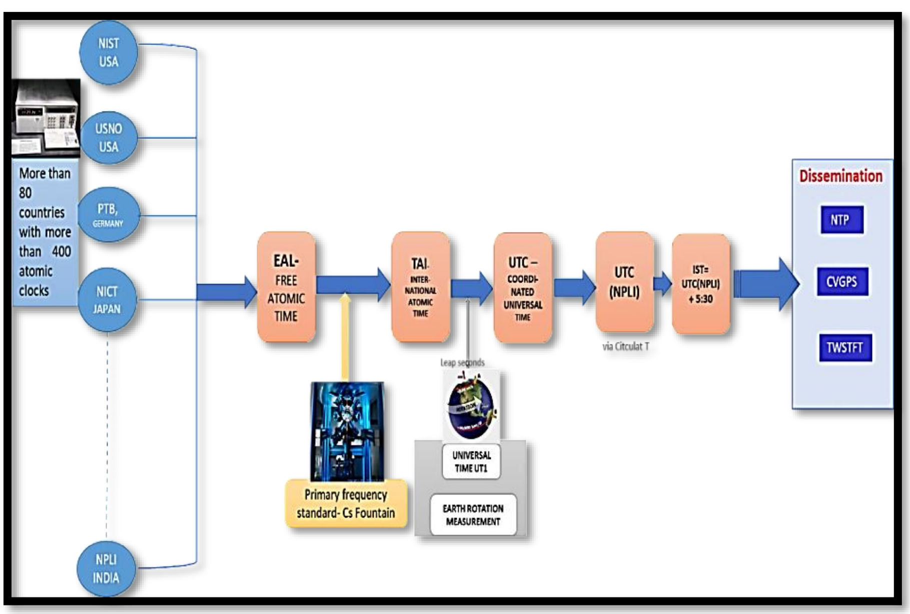

FIGURE 1.1 INTERNATIONAL SCENARIO OF TIMEKEEPING SHOWING SIGNIFICANCE OF NATIONAL TIMESCALE SIGNIFICANCE.

1.4.2 Coordinate Universal Time

1 Majority of the world's NMIs are contributing to UTC by providing readings of their primary reference clocks to BIPM through satellite link. An algorithm (ALGOS) is being used at BIPM to combine the readings of the participating clocks. BIPM produces the international reference UTC every month by taking a weighted average of about 400 free-running high performance atomic clocks located at NMIs, and the clock of NPLI also contribute to it. Leap seconds, as announced by the International Earth Rotation and Reference Systems Service (IERS), are inserted to maintain agreement with the time derived from the rotation of the Earth [29-30]. All the NMIs maintain UTC in regional level, namely UTC (name of the NMI), with respect to the cesium clocks and disseminate "time" and "frequency" to fulfil needs of their own country. Few of the important terminologies used in timekeeping have been explained in Table 1.1.

1.5 Motivation

The systems that are used to develop an ensemble using modern atomic clocks into a single timescale, such as TAI or UTC(k), continue to encounter issues, despite the fact that modern atomic clocks are extremely precise [31]. This research is inspired by the growing need for robust and accurate timekeeping systems, especially as current algorithms such as the weighted average approach with fixed BIPM-assigned weights have limitations under dynamic conditions.

1.5.1 Issues in current timescale generation methods

One way that is frequently utilized is the computation of a weighted average of all of the clocks that are accessible. In this case, BIPM gives each clock a weight that is determined by its stability over the long period [32]. This method is static and does not respond rapidly to sudden clock failures or environmental anomalies, despite the fact that it is effective in settings that are steady. There is no flexibility in real time. In the event that a clock suddenly exhibits irregular behavior (as a result of a malfunction or noise), the influence that it has on the timeline may continue for a longer period of time than is desirable. Clocks that have performance records that are no longer current may be assigned inappropriate weights due to the inflexibility of the weight distribution system. The systems that are already in place are unable to anticipate future performance or identify anomalies in advance. This rigidity can lead to the production of time that is inaccurate in life-critical systems. When it comes to high-frequency trading, for instance, a temporal inaccuracy of even one microsecond might result in financial disparities. The same thing can happen in the field of telecommunications, where a mismatch in time can distort the synchronization of data across continents [33].

1.5.2 Need for robust, adaptive algorithms

The study explores the integration of traditional techniques like Kalman filtering with modern AI and machine learning methods to improve timescale generation [34]. AI can offer predictive capabilities, anomaly detection, and adaptive weighting mechanisms, potentially enhancing timekeeping performance [35]. The goal is to develop a hybrid timescale architecture that ensures accuracy, resilience, and adaptability in national timekeeping systems, addressing both current limitations and future challenges in the domain. This integration aims to enhance real-time anomaly detection, improve clock behaviour prediction, and enable dynamic management of clock ensembles [36]. By combining traditional and AI-based approaches, the goal is to develop a system that is both efficient and adaptable to the complexities of modern data environments [37]. This hybrid framework is intended to strengthen national timekeeping systems while ensuring they remain responsive and resilient to the growing demands of rapidly advancing technologies [38-39]. The research focuses on creating a reliable and resilient timescale algorithm that meets the needs of society today and tomorrow.

1.6 Research Objectives

The following objectives were achieved for the fulfilment of thesis entitled - Design and Development of an Efficient Timescale and its Application:

- Analysis of various Timescale algorithms
- Evaluation of various pre-processing techniques and development of pre-processing algorithm
- Development of Kalman filter-based Timescale algorithm and Application of AI Techniques
- Application of the timescale in dissemination of national timescale

1.7 Problem Statement

Based on the literature study some gaps have been identified in the Timescale development.

1.7.1 Pre-processing Algorithm

Lack of a distinctive preprocessing procedure for the efficient development of Timescale. The most effective method for removing anomalies has not yet been entirely exploited.

1.7.2 Stability of Timescale improvement using efficient timescale algorithm

The current timescale algorithm followed is weighted average method. The stability of the timescale using various algorithms needs to be studied. It can further be improved by developing an efficient algorithm and adopting the same. Best implementation for efficient timescale development is open and yet to be fully exploited.

1.7.3 Adopting latest techniques for Timescale Development:

There is need of adopting latest techniques for timescale development as very few attempts have been made in this area. It is expected that promising performance results can be expected with this techniques-based timescale.

1.8 Scope of Work

This research has advanced the development of robust timescale algorithms and their methods of dissemination; however, it is important to recognize certain inherent limitations and constraints. The research concentrated on methods based on the Kalman filter and AI/ML models, including Support Vector Machines, Random Forests, and Adaptive Neuro-Fuzzy Inference Systems, in addition to certain classical techniques. Other advanced statistical and deep learning architectures, such as reinforcement learning and LSTM ensembles, were not included in the current scope.

Clock Ensemble Constraints: The evaluation focused exclusively on two-year-long data collected at a specific UTC(K) laboratory, having its own constraints. Hence the performance of larger ensembles utilising Cs fountain clocks or optical clocks has not been investigated. Here, the datasets utilised, including CGGTTS, BIPM references, and controlled NTP experiments, were representative yet not comprehensive. The variability arising from various geographic, atmospheric, and network conditions was not comprehensively integrated. Also, this study focused on GNSS All-in-View and NTP-based internet dissemination methods. Alternative dissemination technologies, such as PTP, optical fibre transfer, and long-wave radio services, have not undergone experimental validation.

The proposed framework was primarily validated through simulation and offline analysis. This study did not include real-time hardware deployment (FPGAs, embedded processors), though it is recognized as a potential future direction. While considering aspects of uncertainty and robustness, Although AI/ML models enhanced prediction and stability, their robustness in the face of rare catastrophic events, such as GNSS outages and large-scale cyberattacks on NTP servers are beyond the scope of this PhD dissertation work.

1.9 Thesis Organization

This doctoral thesis features eight chapters, each focusing on a distinct phase of the research, ranging from conceptual foundations to implementation and future objectives.

Chapter one provides an **introduction** and underscores the importance of precise timekeeping in research, technology, and communication, emphasizing the role of national timescales. It presents the rationale for the study, clearly defines the research objectives and problem statement, explores the scope and limitations, and concludes with an overview of the overall structure of the thesis.

Chapter two, the **literature review**, provides a comprehensive examination of both the theoretical and practical foundations of time and frequency standards, covering the SI second, atomic clocks, Coordinated Universal Time (UTC), and International Atomic Time (TAI). The chapter reviews existing timescale algorithms, including ALGOS (BIPM), AT1 (NIST), and ensemble approaches, along with associated pre-processing techniques and their inherent challenges. It further explores the application of Kalman filtering in precise timekeeping and the emerging role of AI and machine learning methodologies in time series modelling. Finally, the chapter identifies research gaps and limitations, setting the stage for the investigations and methodologies presented in the subsequent chapter.

Chapter three focuses on the **analysis of existing timescale algorithms**, evaluating the effectiveness of current time-generation techniques by assessing their strengths and limitations. Key performance metrics such as forecast accuracy, stability, and resilience to anomalies are employed to conduct this assessment. The comparative analysis provides a critical foundation for the design and development of improved algorithms presented in the subsequent chapters.

Chapter four, **data collection and methodology**, outlines the research approach, describing the data sources, preprocessing strategies, and experimental framework employed. The chapter discusses methods for handling noisy clock data, including smoothing techniques and outlier detection, with an emphasis on developing a robust preprocessing strategy aimed at enhancing timescale accuracy and precision.

Chapter five focuses on the **Development of a Kalman Filter-Based Timescale Algorithm**, detailing the design, implementation, and mathematical formulation of the proposed approach. The chapter covers parameter optimization and experimental validation of the algorithm. Performance of the Kalman-based timescale is compared with other existing timescale generation methods, with results demonstrating its superior stability and improved forecasting accuracy relative to traditional models.

Chapter six centres on the **Development of an AI-Enabled Timescale Algorithm**, exploring the application of artificial intelligence and machine learning techniques for timescale generation. Models such as Support Vector Machines (SVM), Random Forest, and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are implemented and evaluated in comparison with conventional methods. Additionally, hybrid approaches that integrate AI with filtering techniques are assessed for their resilience, adaptability, and fault-tolerance, highlighting their potential to enhance timescale accuracy and robustness.

Chapter seven addresses the **Implementation of National Timescale Dissemination**, illustrated through detailed case studies. Two primary distribution methods are examined: satellite-based dissemination using All-in-View GNSS and internet-based dissemination via NTP. The performance of the NIC Hyderabad stratum-1 NTP setup is evaluated against PTB Germany references using CGGTTS data, highlighting the operational effectiveness of the proposed framework in strengthening national timekeeping infrastructure. Additionally, this chapter presents a case study on the remote calibration of the world's largest gnomon sundial to the national timescale, demonstrating practical application and validation of the dissemination methodologies in real-world settings.

Chapter eight, the final chapter on **conclusion and future scope**, summarizes the key contributions of the research, including advancements in preprocessing techniques, the development of the Kalman filter-based timescale algorithm, and the implementation of AI-enhanced models. The chapter also discusses the limitations encountered during the study and outlines recommendations for future work, such as real-time hardware implementation, extensive validation and testing, and potential integration into global timekeeping systems to further enhance accuracy, resilience, and applicability.

Table 1.1 IMPORTANT TERMINOLOGIES USED IN TIMEKEEPING

S. No.	Term	Explanation
1	SI Second	The international standard unit of time, defined using cesium atom oscillations
2	Atomic Clock	A clock that uses the vibrations of atoms (like cesium) for precise timekeeping
3	TAI (International Atomic Time)	Global continuous time scale formed by averaging data from 400+ atomic clocks
4	UTC (Coordinated Universal Time)	Official civil time; adjusted from TAI with leap seconds to match Earth's rotation
5	Leap Second	A one-second adjustment added to UTC occasionally to align with Earth's time
6	Kalman Filter	A mathematical method for filtering noise and predicting future values
7	Ensemble Average	The average of multiple clocks' outputs, weighted based on reliability
8	National Timescale	The official national version of UTC, such as UTC(NPLI) in India.
9	AI in Timekeeping	Use of machine learning for detecting anomalies, forecasting, and optimization

Accurate timekeeping is vital for navigation, communication, banking, research, and national security. Traditional weighted-average methods for generating timescales lack adaptability and robustness, motivating the need for improved approaches. This thesis addresses these challenges by developing robust preprocessing techniques, Kalman filter–based algorithms, and AI-driven models to enhance precision, stability, and anomaly detection, ensuring reliable national timescales for critical infrastructures and emerging technologies. The background traces timekeeping's evolution from ancient instruments to atomic standards, establishing its strategic importance. The thesis is organized into eight chapters, progressing logically from foundations to applications and future scope.

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Chapter - 2

Literature Review

This chapter reviews the theoretical and practical foundations of time and frequency standards, including atomic clocks, SI second, UTC, and TAI. It examines existing timescale algorithms, preprocessing methods, and the application of Kalman filtering and AI/ML techniques, identifying research gaps that guide the objectives of the current study.

2.1. Introduction

The literature review chapter has been structured into six parts

2.1.1. Time and Frequency Standards Overview

This section covers UTC and TAI developments, leap seconds, National realizations', global view, Optical clocks and future trends and Social/heritage perspectives.

For thousands of years, people have studied time and how to measure it. It started with cultural practices and astronomical observations and has grown into the advanced atomic standards we use today. *Whitrow*, gives an intellectual and historical basis by looking at how ancient cultures thought about and organized time [40]. He shows that early time systems were shaped by philosophical, religious, and practical needs. This focus on cultural roots is important because it puts the scientific quest for precise measurement in a broader context, showing that it is not just a technical issue but a basic response to people's needs for coordination and order. *Kartaschoff* built on these historical insights by creating a systematic classification of time scales that separates astronomical, atomic, and physical constructs [41]. His framework is methodologically important because it gave a way to look at and compare different ways of keeping time. This made it possible for later metrological communities to bring all of their measurement systems together under one taxonomy. *Vigo and Frattolillo,* added to this cultural and technical conversation by talking about the historical and social effects of measuring time [42]. They said that advances in metrology cannot be separated from the social systems that use and rely on them.

The switch from astronomical to atomic time was one of the most important changes in this field. *Panfilo*, talks about how Coordinated Universal Time (UTC) has changed over time [43]. UTC is a combination of International Atomic Time (TAI) and data on how the Earth rotates. This method is based on both the Bureau International des Poids et Mesures (BIPM)'s statistical processing and operational strategies. *Seidelmann and Seago*, go into more detail about this by talking about how leap seconds are added to atomic timescales to make them fit with irregular astronomical cycles [44]. Their research also shows how leap seconds can mess up navigation and communication systems, which shows the tension between accuracy and usefulness. *McCarthy, Nelson, and Hackman* go into more detail about the geophysical causes of leap seconds by showing quantitative models of how the Earth's rotation is not always regular [45]. They also show that geophysical variability makes even the most stable atomic references less reliable. These three studies show that building a timescale is an interdisciplinary task that must take into account physical realities, technical limitations, and social needs.

The institutional improvement of UTC has also been very important for global synchronisation. *Panfilo and Arias*, talk about UTC's modern computational architecture, which is based on weighted clock ensembles and better ways to estimate uncertainty [46]. Their study shows that robust statistical weighting reduces the effect of unusual clock behavior, making the international standard more stable and accurate.

Agnew, on the other hand, added a new environmental aspect to this discussion by showing how climate change and global warming affect the Earth's rotational parameters, which pushes back the expected leap second adjustments [47]. The connection between environmental science and timekeeping shows a new area of research in the field. It also shows that metrology can't be separated from changes happening on a larger scale on Earth.

At the national level, changes in timescale realization show even more how different methods and new technologies are being used. *Bauch et al*. recorded the German implementation of UTC(PTB), a national standard based on cesium fountain clocks [48]. Their work explains how to add primary frequency standards to UTC, which caused uncertainties of about 10^{-16}. This was a big step forward in architecture compared to earlier cesium beam implementations. *Yuan et al*. said that China's NTSC made similar progress by combining cesium standards with hydrogen masers [49]. The method took advantage of the fact that masers are very stable in the short term and cesium is very accurate in the long term. It showed that hybrid ensembles can achieve mid-term stability at the 10^{-15} level. These contributions show that ensemble design and clock weighting strategies not only improve performance, but they also affect global UTC calculations by being used in BIPM algorithms.

The Indian context gives us more historical and modern information about how to keep time. *Thorat, Agarwal, and Aswal* look at India's contributions from ancient observational astronomy to its current role in UTC [50]. They show how cultural heritage and modern precision standards are connected. *Kumar*, looks closely at the 18th-century observatories built by Sawai Jai Singh, which were examples of architectural innovation in the quest for accurate solar measurements [51]. These early observatories were the first steps towards systematic astronomical metrology. They show that designing buildings and instruments was just as important to early timekeeping as algorithms are now. *Aveni*, on the other hand, looks at India's and other civilizations' efforts in a larger context, looking at how calendars, observatories, and cultural practices affected how societies organized their time [52].

The overall results of these studies show that there has been both continuity and change in the development of time and frequency standards. The shift from astronomical classifications to statistical weighting in UTC exemplifies the growing complexity of algorithmic and ensemble methodologies. New ideas come from research that connects changes in the environment to timekeeping or shows how fountain clocks work better. UTC(PTB) achieved uncertainties at the 10^{-16} level, and NTSC ensembles achieved mid-term stability around 10^{-15}. This shows how technological progress has made real improvements. Historical studies, offer vital continuity, illustrating that the quest for accurate time has consistently been both a technical and cultural pursuit. The persistent issues regarding leap seconds, demonstrate that, despite such accuracy, global consensus and unobstructed distribution have yet to be achieved. These basic talks directly lead to the study of advanced timescale algorithms, which try to get around these problems and will be talked about in the next section.

The literature illustrates that timekeeping is both a scientific and societal construct, impacting areas well beyond metrology.

2.1.2. Timescale Algorithms

This section covers, early algorithmic approaches, national timescales: AT1, AT2, ALGOS, A.1, applications in satellite/GNSS timescales, Recent developments at NMIs and Tools for noise/statistical analysis.

The development and implementation of algorithms for making and improving timescales is a major focus of modern time metrology. Time standards depend on stable frequency sources, but the algorithmic processes determine how these sources are combined, directed, and weighted to create a scale that is always accurate. Initial contributions to this discipline established the groundwork for enduring innovations. Thomas and Azoubib, in a groundbreaking study on TAI computation, examined the effects of establishing a maximum threshold on clock weights [53]. Their research showed that while weighting strategies are necessary to prevent one clock from taking over, constraints must be carefully planned so that they don't make the ensemble less stable. Their method involved running computer simulations to compare unrestricted and bounded weighting. The results showed that weight caps make things more robust against anomalies, but they also make things a little less stable in the short term. This approach had a direct effect on later BIPM practices by stressing the balance between accuracy and resilience.

Stein, made a big step forward in this field by giving a full analysis of timescale algorithms at the 24th PTTI meeting [54]. He systematically examined methodologies for integrating clock ensembles, emphasising the statistical principles underlying Kalman filtering, smoothing, and extrapolation. Stein's innovation was the introduction of adaptive weighting mechanisms that dynamically adjust to variations in clock performance, serving as a precursor to contemporary methodologies employed in robust ensemble design. Significantly, his findings demonstrated that adaptive methods could attain fractional frequency stabilities within the 10^{-14} to 10^{-15} range, which, at that time, indicated a notable advancement compared to fixed-weight strategies. *Stein's* research shows that algorithm development is an iterative process in which being able to handle clock behaviour anomalies is just as important as reducing measurement noise.

The growing accuracy of atomic standards, especially hydrogen masers, led to more improvements in algorithmic integration. *Jiang, Dong, and Wu* examined a timescale algorithm utilising hydrogen masers, capitalising on the superior short-term stability of masers for guidance [55]. Their method used ensemble averaging and prediction algorithms to make up for drift and ageing, which made the scales stable in the middle term, which was better than traditional cesium-based scales. The study measured Allan deviations in the 10^{-15} range over averaging periods of 10^3 to 10^4 seconds, showing that using maser ensembles to build timescales is better in terms of numbers. Their work was a step forward in using different clock features to improve performance in different ways.

The rise of optical clocks, which reduced uncertainties to the 10^{-18} level, marked a major advance in algorithmic design. *Ido et al.* documented the inaugural experimental implementation of a time scale regulated by an optical clock [56]. They used hybrid algorithms that combined short-term maser stability with long-term optical accuracy to combine optical clock data with existing ensemble methods. This work was new because it showed that steering algorithms could be expanded beyond microwave standards to include optical frequencies. This was an important step towards redefining the second. The results indicated that an optical-clock-steered scale significantly surpassed maser-only scales, attaining fractional frequency instabilities nearing 10^{-17} over a one-day period. This was not only a step forward in algorithms, but also a big step forward in technology that connected optical and microwave domains.

Yao et al. built on these improvements by introducing an optical-clock-based time scale that made it possible to combine multiple optical references into ensemble algorithms [57]. They used advanced prediction and steering algorithms to keep things going when the optical clock was down. They did this by combining optical lattice clocks with hydrogen masers. Their results showed that performance was at the level of 2×10^{-17} over averaging times of 10^5 seconds, which proved that optical timescales could be used for national standards. Their architecture was important because it solved the practical problem of intermittent optical operation, which was a new idea that made sure it would work in the real world. This progress signalled a shift from experimental demonstrations to functional prototypes, illustrating the evolution of algorithms in tandem with hardware advancements.

These studies collectively underscore the significance of algorithmic strategies in the development of timescales. Early works underscored the necessity for robustness and adaptability, reconciling resilience with stability. The combination of hydrogen masers showed how new algorithms could take advantage of different types of hardware, while steering optical clocks showed a new area where algorithms connect two very different frequency domains. These advances have led to measurable improvements, with adaptive methods achieving stability levels from 10^{-14} to 10^{-15} and optical integration achieving performance levels from 10^{-17} to 10^{-17}. The progression in architecture shows a move away from static weighting and towards dynamic, predictive, and hybrid approaches. This shows how computational models for timekeeping are becoming more advanced.

The review of timescale algorithms is also very similar to the bigger ideas that were brought up in “time and frequency overview” section earlier. Just as UTC's institutional management needed weighting schemes and resilience against anomalies, algorithmic advancements are the computational backbone that makes sure the international timescale is both accurate and strong. The switch to optical references is similar to past changes in culture and institutions. It is a change in method that is just as important as the switch from astronomical to atomic standards. The literature on timescale algorithms shows that the future of accurate timekeeping depends just as much on computer intelligence as it does on the performance of physical clocks. This directly encourages more research into preprocessing techniques, Kalman filtering, and AI-driven methods that will be discussed in the coming sections

2.1.3. Clock Data acquisitions and Pre-Processing Techniques

This section of literature review convers, Noise/anomaly detection in atomic clocks with Statistical filtering approaches. To make reliable timescales, it's necessary to use the right algorithms to combine data and preprocess clock data to find, fix, and prevent problems. Preprocessing makes sure that the ensemble inputs don't have any false measurements, noise artefacts, or sudden discontinuities that could make the output timescale unstable.

50 *Galleani and Tavella* made one of the most important contributions to this field by coming up with methods for finding and identifying problems with atomic clocks [58]. Their research employed statistical methodologies grounded in residual analysis and variance monitoring to identify frequency jumps, phase shifts, and other nonstationary behaviors. By testing their algorithms on real clock datasets, they showed that preprocessing could find unusual events without changing nominal performance too much, which made timekeeping ensembles more stable.

Wang and Rochat, expanded the identification of anomalies by introducing a robust clock anomaly detection algorithm specifically designed for ensemble timekeeping [59]. Their method focused on being able to handle false positives by using cross-correlation between clocks and setting adaptive thresholds based on ensemble variance. This was especially new because it dealt with the fact that anomalies might not show up in the record of a single clock, but they can be figured out by looking at how the whole group behaves. Their results, which were tested in simulations of robust ensemble generation, showed that their method was more stable and continuous than previous methods for rejecting anomalies. This was a big step towards making preprocessing frameworks that are both fault-tolerant and minimally disruptive to how ensembles work. More improvements were made to how clocks behave when they are in motion. *Galleani and Tavella*, presented the dynamic Allan variance (DAVAR) as an instrument for examining time-varying frequency stability [60]. The traditional Allan variance assumes stationarity, but DAVAR lets you look at stability over short, sliding windows, which lets you see behaviors that change quickly and environmental sensitivities. Their method included both theoretical formulation and real-world examples that showed how DAVAR could find trends in hydrogen masers and cesium clocks that would be hidden by averaging. This progress gave the preprocessing community a way to tell the difference between normal behavior and hidden problems, which helped with better forecasting and filtering in later stages of the algorithm.

Preprocessing techniques have also gotten better by using signal processing methods from statistics and engineering. *Pearson et al*. presented generalized Hampel filters as a resilient method for identifying outliers [61]. Their method builds on the classic Hampel identifier by adding tunable sensitivity parameters and adaptive thresholds to find non-Gaussian noise and impulsive errors. The new thing is that it can get rid of localized outliers without messing up the underlying signal. This is very important when working with clock data, where sudden but rare anomalies can happen. Their findings, confirmed on both synthetic and real datasets, showed that generalized Hampel filters are better than simple moving-average techniques at keeping the signal intact while getting rid of spikes. These contributions underscore the increasing significance of advanced signal processing in the preprocessing of atomic clock records.

Kordestani and Zhang, examined the direct utilization of the Savitzky–Golay filter for clock anomaly detection and rectification, thereby complementing this research trajectory. Savitzky–Golay smoothing, on the other hand, fits local polynomials to segments of data, which keeps higher-order features like slope and curvature [62]. The Hampel filter, on the other hand, rejects outliers. Their method clearly compared filtered clock series to unfiltered ensembles, showing that it was better at finding small frequency drifts and reducing noise without causing a lot of phase distortion. This new idea combined traditional smoothing methods with clock-specific needs, which led to measurable improvements in short-term frequency stability. Their results show that using the right preprocessing techniques can lower Allan deviations by a significant amount, which will improve both prediction and ensemble stability.

These studies show how preprocessing has changed over time, going from finding anomalies to dynamic characterization and strong filtering. Methodologically, they demonstrate an evolution from statistical variance monitoring to sophisticated filtering and adaptive thresholds. Preprocessing has moved from clock-centric analysis to ensemble-aware methods in architecture. This is because it is easier to understand anomalies when they are compared to other things. Quantitative outcomes, including diminished Allan deviations and enhanced ensemble robustness, illustrate the significant influence of preprocessing on the efficacy of national timescales. Simultaneously, the literature highlights a significant research deficiency: despite the introduction of various filtering techniques, a universally accepted preprocessing standard remains absent. The lack of standardized algorithms leads to differences in national timescale performance and opens the door for new AI- or Kalman-based preprocessing methods that could bring the field together.

Preprocessing is the most important link between clock behaviour and algorithmic construction when it comes to interconnection. Just like weighting strategies or optical steering, which depend on accurate input, preprocessing makes sure that errors don't carry over into final timescales. The methods discussed here not only improve robustness, but they also set the stage for the best estimation methods, like Kalman filtering, to work well. The trajectory of preprocessing research underscores that dependable timekeeping hinges not solely on high-performance clocks or intricate algorithms, but also on data integrity, prompting the investigation of advanced estimation frameworks in the subsequent section.

2.1.4. Kalman Filtering in Timing Applications

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This section provides a review of the theoretical foundation, among other topics. The use of Kalman filters has become an important method for modelling, forecasting, and controlling time and frequency in systems that need very precise timing. *Panfilo and Arias* offer a comprehensive, metrology-centric discussion on optimal estimation in atomic timing, presenting a state-space framework where clock phase and frequency (and optionally drift) are designated as states, while time-difference measurements function as observations [63]. Methodologically, they elucidate the integration of process noise models for various clock types (e.g., hydrogen masers versus caesium) into state evolution, and how measurement noise covariance dictates the weighting of observations. A significant architectural theme in their analysis is that Kalman filters integrate prediction and smoothing into a singular framework, facilitating both real-time navigation and retrospective performance evaluation. They stress that process/measurement covariances are not random; they are linked to clock-noise characterisations and transfer-link uncertainties. This means that the filter's quality depends on how well the model matches the real world. So, the new thing here isn't just one new algorithm; it's a whole engineering framework that brings together noise modelling, estimation, and control for timing issues.

Kalman filters have been examined as substitutes for conventional control-loop architectures at the network and IT periphery. *Bletsas* examines Kalman filtering for network time synchronisation, necessitating the integration of timing packets and local oscillator dynamics to ascertain a machine clock's offset or skew in relation to a reference [64]. The method creates a linear state-space model of the local oscillator (phase and frequency error) and then uses noisy measurements that are affected by delays (like NTP-like exchanges) to update that model. This replaces heuristic PLL-like adjustments with statistically sound gains based on covariances. The most important finding is that Kalman filtering can lower jitter and make things more stable compared to baseline algorithms, especially when network delay changes, because it clearly separates oscillator noise from measurement noise and uses prediction when observations are not very good. The contribution is pertinent to any system that transmits time over flawed networks, anticipating subsequent industry transitions towards model-based servo designs.

In the context of national timescales and clock ensembles, specialised Kalman variants have been suggested to reconcile short-term smoothness with long-term fidelity. *Greenhall* discusses "reduced" Kalman filters for clock ensembles—changes that change how covariance is handled to lessen the tendency of a standard filter to give up short-term smoothness in favour of long-term optimality [65]. The reduced filter changes the error covariance between updates to keep aggressive corrections from putting short-term noise into the timescale. This fits well into ensemble operations where many clocks with different types of noise have to be combined to make a single steered scale. The new thing is that the filter's short-term behaviour is designed explicitly, while still keeping the long-term benefits of Kalman estimation. The outcome indicates a more "stiff" timescale, meaning one that is less affected by individual clock quirks, while still following the ensemble's long-term trend.

Integrating autonomous health monitoring into the Kalman framework is a crucial system-level advancement. *Yao, Parker, and Levine* present a Kalman-filter time scale (JY1) in which anomaly detection is built into the estimation loop [66]. The design methodologically tracks filter innovations and residuals to find time or frequency steps and automatically lower the weight of clocks that are suspicious. This architecture recognises that clocks sometimes have steps or periods of bad behaviour; by embedding detection in the filter, it makes it possible to quickly fix the problem without having to do anything manually. The novelty is twofold: (i) a timescale governed by a Kalman estimator, and (ii) self-regulating clock quality based on internal statistical tests. The results show that the scale is more robust and stable when used, while still being closely aligned with external references. This is especially important when the conditions for measuring or processing change or when a small number of clocks show temporary faults.

As timing labs use more and more intermittent references, like primary standards or optical clocks that aren't always available, Kalman filters naturally expand to multi-observation fusion. *Wang et al.* present a robust timekeeping algorithm that integrates various observation sources within a Kalman framework, specifically addressing intervals of reference "dead time" [67]. The filter accepts different types of observations (like fountain or optical references along with maser ensemble data) and keeps a consistent state estimate through gaps by using well-tuned process models. This is a principled way to combine the short-term stability of masers with the long-term accuracy of primaries and optics that are only available sometimes. The new thing is the explicit multi-observation design that is meant to be resilient: the timescale stays well-behaved even when premier references drop out for a short time. The results show that single-observation designs can be improved in measurable ways and that continuity and stability can be maintained even when a primary reference is out for a long time. Kalman reasoning is also important for GPS-disciplined and satellite-referenced systems that use external time to sync up local oscillators.

Giffard says that using a fixed, L1 C/A-code GPS receiver makes it easier to get UTC (USNO, MC) back [68]. The receiver and processing chain are simpler than today's multi-frequency PPP methods, but the basic idea of using a Kalman formulation to discipline a local oscillator to a “spaceborne” reference and model the composite noise works well. The key point is that even with a simple receiver, algorithmic discipline and modelling can make a big difference in how well the system aligns with UTC(USNO).

This job links ensemble filters in labs to real-world dissemination endpoints, where model-based estimators act as a bridge between local oscillators and imperfect external references.

There are a few themes that connect these contributions. First, Kalman filters give timing a common language. This includes lab ensembles, autonomous timescales with built-in anomaly handling, multi-observation resilience, and networked synchronisation. Second, improvements to the architecture are important: Reduced-covariance strategies adjust short-term smoothness; innovation monitoring allows for automatic clock quality control; and fusion filters handle intermittent references without losing long-term accuracy. Third, these methods don't work on their own; they need good preprocessing and noise characterisation (as we talked about in the Preprocessing section), and they lead to problems with dissemination (which we will talk about in the AIML section).

These investigations collectively affirm that Kalman filtering is robust, accurate, and sufficiently adaptable to remain pivotal in both contemporary and emerging timekeeping applications.

2.1.5. AI and ML Techniques in Time Series and Timescale Generation

This review section is regarding the literature finding for neural networks in timescale prediction, Fuzzy/neuro-fuzzy timescales, ML in navigation/time series, Ensemble ML approaches, Broader AI applications.

The increasing degree of difficulty of timescale generation and the growing amount of
47 clock data have made it possible for artificial intelligence (AI) and machine learning (ML) methods to add to or improve classical approaches. AI methods can find nonlinear patterns and change as datasets change, which makes them great for forecasting, finding anomalies, and hybrid timekeeping applications. This is different from deterministic algorithms or statistical filters.

One of the first clear attempts to use neural networks to predict timescales is by *Sobolewski and Miczulski*. They used feedforward neural architectures to guess certain national scales based on input data from UTC and UTCr. Their approach is new because it sees timekeeping not just as a statistical problem but as a pattern-recognition task, where historical offsets can be used to learn nonlinear dependencies. They demonstrated experimentally that neural networks could diminish prediction error relative to linear models, facilitating more seamless extrapolations during instances of erratic clock behaviour. The initial findings indicated that neural predictors could enhance ensemble techniques by adding an extra level of reliability [69].

The investigation of AI in analogous domains has yielded methodological insights for timekeeping. *Barszcz, Bielecki, and Wójcik* presented ART-type (adaptive resonance
31 theory) neural networks for the classification of operational states in wind turbines [70]. Their main goal was to monitor conditions, but the new thing was showing how unsupervised neural structures can group and label system states without needing explicit training labels. The architectural similarities are very clear: Atomic clocks show drift and instability that happen before anomalies, just like turbines show small changes in state that happen before failures. Their results suggest that it is possible to use clustering and classification methods from industrial monitoring in time metrology, where finding strange clock states early on could make preprocessing pipelines stronger.

54 *Liao et al.* proposed a neural-fuzzy system to create a "paper time scale" for
170 Eastern Asia, which was a more direct use of AI in timekeeping [71]. They used a combination of neural networks and fuzzy logic rules to make a regional timescale that took into account the different contributions of local clocks. This hybrid architecture solved two long-standing problems: how to predict clock drift in a nonlinear way and how to deal with uncertainty in measurement links. The innovation lay in formalising a distributed, AI-enhanced model of regional coordination that connects national timescales without depending entirely on centralised algorithms. At the joint IEEE FCS and EFTF meeting, they showed that neural-fuzzy models could replace traditional averaging methods, making continuity better even when the quality of the input is different.

AI has many uses beyond just keeping track of time. It also shows architectural strategies that can be adapted to different timescales. *Doshi et al*. examine the function of AI in cloud performance and data security, offering frameworks for overseeing distributed infrastructures via predictive and adaptive intelligence [72]. This isn't a paper about keeping time, but it's still important because more and more, time dissemination depends on cloud-based infrastructures and virtualised services. Their research shows how AI can dynamically allocate resources, find problems, and adapt to changes in real time. This can help with designing resilient dissemination architectures. When used for managing timescales, similar methods could make sure that distributed timing nodes stay in sync even when the load changes or there are problems.

These studies show that AI and ML are useful but not widely used tools for keeping time. *Sobolewski and Miczulski*] showed that neural networks can improve predictive accuracy [69]. *Liao et al*. showed that hybrid architectures can make timescales more resilient by dividing them into regions [71]. *Barszcz et al*. [70] and *Doshi et al*. [72] presented parallels from condition monitoring and cloud management, emphasising that anomaly detection and adaptive intelligence can be applied to clock ensembles and dissemination networks. But the literature also shows that there are some big holes. Most implementations are proof-of-concept rather than standardised frameworks, and only a few have been tested against the scale and rigour of international UTC generation. Quantitatively, although decreases in prediction error and enhancements in continuity are documented, extensive statistical benchmarks are still limited. There is also not much architectural integration between AI models and the Kalman-based systems that are most commonly used today, which makes it hard for them to be used right away.

This literature review summarizes that, Pre-processing studies concentrate on statistical anomaly detection; however, AI provides nonlinear, adaptive alternatives that may identify more nuanced patterns. Kalman filtering offers strong model-based estimation, but AI could make it better by learning noise models based on data or by dynamically adjusting filter parameters. As dissemination networks become more distributed and reliant on the cloud, AI methods used in infrastructure monitoring could help keep track of timing across different platforms. So, even though AI in timescales is still a new field, the literature we've looked at shows that it's both possible and necessary:

Intelligent systems could fill in the gaps that keep coming up in preprocessing, estimation, and dissemination continuity.

2.1.6. Time Dissemination Techniques

The distribution of accurate time is the ultimate and most pragmatic measure in the implementation of national timeframes, guaranteeing accessibility for scientific, industrial, financial, and defense purposes. Over the decades, dissemination methods have progressed from long-wave radio broadcasts to telephone services and currently to internet-based protocols like the Network Time Protocol (NTP). Each method demonstrates a balance among cost, accessibility, accuracy, and technological preparedness.

VoBa, Ulland, Lombardi, and Lentfer emphasise the necessity of re-evaluating timekeeping to accommodate the requirements of contemporary IT systems [73]. Their research, presented at the 2019 PTTI meeting, contends that dissemination must evolve to accommodate distributed computing, cloud infrastructures, and cybersecurity
35 imperatives. Methodologically, they evaluated the interaction of Network Time Protocol (NTP) and Precision Time Protocol (PTP) with enterprise architectures, pinpointing vulnerabilities and bottlenecks. A major new idea is their plan for hybrid dissemination systems that combine traditional GNSS references with secure internet protocols. Their findings underscore that precision alone is inadequate—security and resilience must also be integrated into dissemination channels, a theme that is becoming increasingly critical as essential infrastructure relies on synchronized timing.

Weaver and Kantsiper, also look at what future lunar and planetary navigation systems will need to be able to ensure [74]. Their research creates theoretical models for disciplined timekeeping systems that can work in deep-space environments where latency, relativity, and coverage are all problems. They looked at spacecraft navigation architectures and came up with disciplined oscillators that are controlled by atomic standards on Earth but can work on their own when there are communication gaps. Their innovative approach consists of modifying traditional disciplinary techniques to suit extraterrestrial environments, indicating potential dissemination difficulties for human exploration beyond Earth's orbit. The findings indicated that lunar missions necessitate hybrid systems integrating local oscillators and interplanetary links, thereby confirming the viability of extending accurate time dissemination beyond Earth.

Internet-based protocols still play a big role in how information spreads on land. *Gamage et al*. put forward a flexible framework for Internet-based NTP services [75]. Their research examines current architectures, pinpointing deficiencies in scalability and susceptibility to delay attacks. In terms of methodology, they created a model that changes NTP parameters on the fly based on how the network is behaving, which lowers jitter and makes it more accurate. This work is new because it looks at NTP as an adaptive, intelligent framework that can change with the environment instead of a fixed protocol. The results showed that synchronization accuracy improved across different types of networks, which provided quantitative proof of adaptive strategies. This is a link between older ways of sharing information and newer, AI-enhanced systems.

Satellite-based dissemination continues to support UTC recovery at user sites. *Giffard* talked about how using a fixed L1 C/A-code GPS receiver made it easier to get UTC (USNO, MC) back with better accuracy [76]. His research showed that even with simple GPS hardware, disciplined oscillator architectures and optimized processing could get better alignment with UTC. The new thing is that dissemination improvements aren't just for advanced multi-frequency systems; algorithmic discipline can get higher accuracy from older receivers as well. This finding is still important for places where high-end receivers aren't available but reliable. UTC access is very important.

Matsakis, Defraigne, and Banerjee, offer a comprehensive examination of precise time and frequency transfer, exploring techniques that include GNSS common-view and Two-Way Satellite Time and Frequency Transfer (TWSTFT) [77]. Their methodological contribution consists of quantifying uncertainties across various methods and evaluating long-term stability. Their findings corroborate that GNSS methodologies can attain sub-nanosecond precision under optimal circumstances, whereas TWSTFT provides resilience against ionospheric influences. The new idea is to show a comparison of different ways to spread information, focusing on the trade-offs between accuracy, cost, and resilience. Their synthesis continues to serve as a fundamental reference for the formulation of dissemination strategies, integrating laboratory accuracy with user requirements.

Studies on how information spreads on the internet have also grown to include metrological analysis. *Kumar et al.* assessed global NTP services within the framework of metrology, contrasting them with conventional dissemination systems [78]. They measured the latency and stability of NTP servers in different parts of the world to come up with quantitative benchmarks for synchronization performance. They came to the conclusion that NTP is good enough for most IT tasks, but it needs improvements to work well for high-precision metrology. The new thing here is that it treats internet dissemination not just as an IT service but also as a metrological infrastructure. This shows where there are still gaps between laboratory standards and services for the general public.

Lastly, *Piester et al. and Feldmann* look into spreading information through satellite and optical fibre links [79] [80]. *Piester's* team showed how bidirectional satellite links and stabilized optical fibers can be used to synchronize atomic clocks from a distance. Their method measured and compared link uncertainties, showing that fiber-optic dissemination can reach picosecond-level performance, which is much better than satellite-based methods.

Feldmann's doctoral research offers an in-depth examination of GPS-based dissemination for metrological applications, focusing on sophisticated receiver calibration and algorithmic compensation [80]. The innovation of these works resides in illustrating that dissemination is dynamic: emerging mediums, such as stabilized fibers, are redefining the performance envelope, facilitating laboratory-grade time transfer across national and continental dimensions.

These contributions together show how things have changed over time. Early dissemination systems, such as GPS C/A-code receivers, illustrate that even outdated hardware can gain from enhanced modelling, whereas comparative studies evaluate current methodologies against contemporary standards. Adaptive frameworks and hybrid architectures demonstrate the incorporation of resilience and security into dissemination, whereas extraterrestrial concepts expand the scope to lunar missions. Fiber-optic systems and advanced GPS research are at the cutting edge, bringing the standards used in labs and by field users closer together. In terms of numbers, dissemination accuracies have gone from nanoseconds to picoseconds, which shows how amazing the progress has been. But there are still gaps to make sure that information is always available, verified, and accessible to everyone is still an open research problem, especially since global infrastructures need both ultra-high precision and constant availability

The literature indicates that dissemination tactics are as essential as the algorithms governing the timescale. Each NMI optimally balances accessibility, robustness, and precision in selecting dissemination options. Although long-wave radio maintains a dependable foundation for consumer electronics and NTP prevails in the digital realm, the incorporation of AI-augmented timeframes into these distribution systems is still an unexplored area of research.

Summery

The literature examined across six thematic domains underscores the significant advancement of time and frequency metrology—from initial investigations of astronomical and atomic standards to the development of timescale algorithms, preprocessing techniques, Kalman filtering, artificial intelligence applications, and dissemination strategies. These investigations show that while new hardware like hydrogen masers and optical clocks have made stability much better, the actual power of modern timeframes comes from algorithmic intelligence, preprocessing resilience, and dissemination dependability. However, a common thread in the studies that were looked at is the lack of a standardised, efficient preprocessing framework that can easily combine intelligent estimates, adaptive filtering, and anomaly detection. Current techniques depend on a mix of statistical methods, Kalman variants, and new AI tools. However, there is no single system that can ensure resilience, adaptability, and accuracy at the same time. The expanding demands for continuous and secure time dissemination to terrestrial, cloud, and even extraterrestrial domains render this gap even more critical. The next step in timekeeping research is to create an efficient timescale framework in which preprocessing algorithms, improved by Kalman filtering and AI/ML methods, are the basis for a strong, scalable, and universally accessible timing infrastructure.

This chapter reviewed the current state of research on time and frequency standards, timescale algorithms, and preprocessing techniques. It covered both theoretical foundations and practical implementations, highlighting emerging methods such as Kalman filtering and AI/ML approaches. Key research gaps were identified, providing a basis for the methodologies and investigations presented by the authors

Chapter 3
Analysis of Existing Timescale Algorithms

This chapter examines the critical role of timescale systems in precise timekeeping for telecommunications and global navigation. It highlights the integration of atomic clocks, algorithmic modules, and distribution networks, discussing methodologies by BIPM and NIST. Key performance metrics, composite timescales, and a comparative analysis of seven prominent algorithms are reviewed, emphasizing the selection of appropriate approaches based on accuracy, stability, and operational requirements.

3.1. Introduction

146 This chapter explores the critical role of timescale systems in achieving precise timekeeping for telecommunications and global navigation. It examines the integration of atomic clock networks, data collection units, and algorithmic modules, highlighting methodologies developed by BIPM and NIST. Key concepts such as composite timescales, performance metrics, and the comparative analysis of seven prominent algorithms are discussed, emphasizing the importance of selecting timescale methods that balance accuracy, stability, and computational efficiency for modern technological applications

3.1.1. Architectural Time Scale Systems

Time scale systems are carefully designed to create a constant and stable reference for keeping time by combining the outputs of many atomic clocks. These systems are very important for making sure that things are accurate in a wide range of fields, from telecommunications to global positioning systems. By combining several atomic clocks, it is possible to reduce the differences between them, which makes the time reference more reliable and accurate as a whole. Time scale systems can average the outputs of these atomic clocks by using advanced algorithms and methods. This creates a time standard that is both stable and resistant to changes [81].

The time reference must be continuous to be utilized as a standard across different platforms and technologies. Furthermore, the time reference must be extremely reliable

for scientific research and many commercial applications, as even minor changes can
35 lead to major errors. The design and operation of time scale systems demonstrate how vital accuracy is in today's environment. They make many technological advances possible and make sure that keeping track of time is still an accurate and reliable task. These systems consist of several essential elements from an architectural perspective. These consist of clock ensembles that function as the system's time backbone, data acquisition units that acquire and process pertinent information, algorithmic modules that are employed for estimation and predictive analysis, and output distribution channels that facilitate the dissemination of the results.

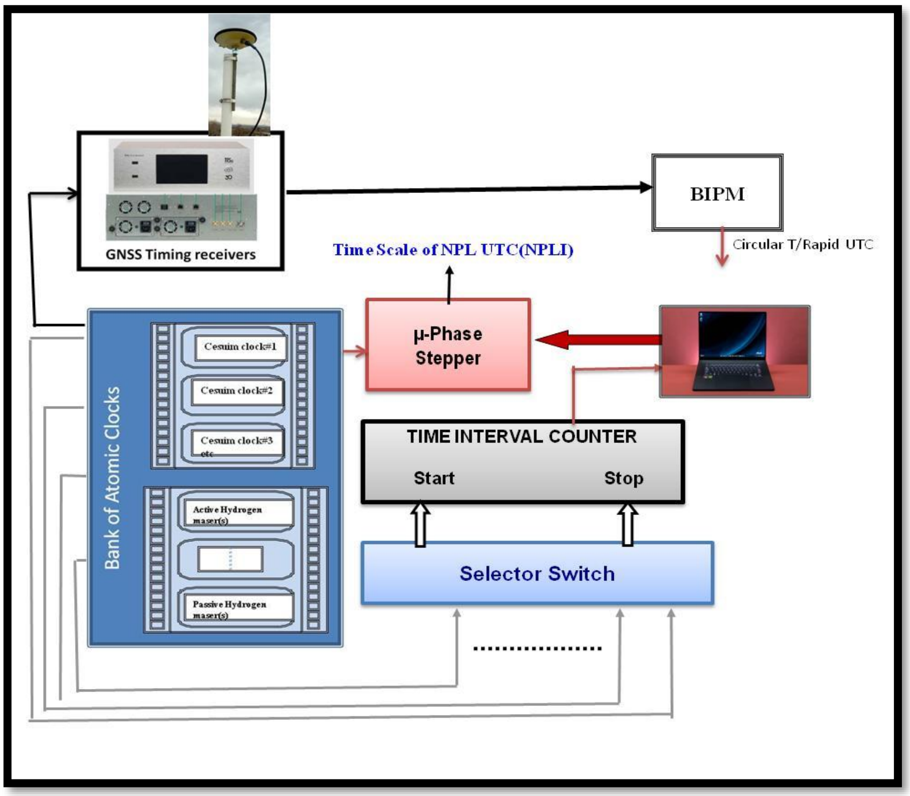

FIGURE 3.1 ARCHITECTURE OF TIMESCALE

These parts are all very important to how well the system works and how well it communicates, processes, and stores data. For the system to work well in its intended context, these parts need to work together in the right way. The clock ensembles keep everything in sync, which is important for making sure that all the modules work together. In the meantime, the data acquisition units have the important job of collecting data from many different sources and making sure that the information sent to the algorithmic modules is both relevant and up-to-date. The algorithmic modules are very important because they use advanced methods to look at the data that comes in, make estimates, and make predictions based on models that have already been set up. Lastly, the output distribution channels are in charge of National Metrology Institutes (NMIs) using different architectural frameworks that are carefully aligned with their specific operational goals. One such architecture is shown in Fig. 3.1. The choice of these architectures is not random; it is a careful process that takes into account the specific roles and responsibilities of each institute. NMIs can do a better job in the field of metrology by designing their structures to meet specific needs. There are many different design methods used in systems like USNO A.1, BIPM ALGOS, and NIST TA [82]. These methods range from simple averaging methods to more complicated adaptive filtering methods. Each of these systems has its own focus on important features like stability, reliability, and the ability to process data in real time. The differences between these systems show how complex timekeeping and synchronisation technologies are, which are important for many scientific and practical uses. The choice of a certain system often depends on the specific needs of the job, such as how accurate it needs to be, how well it can keep performing consistently in different situations, and how quickly it needs to respond to changes in the environment. Because of this, the design and use of these systems show that the trade-offs involved in getting the best performance in different operational situations have been carefully thought out. These technologies keep changing to help us learn more about measuring time and to understand fields like astronomy, telecommunications, and global positioning systems [83]. In a nutshell, examining these systems underscores the significance of advancing technologies for precise timekeeping while also promoting further research into the principles underlying their design and operation. This continuing discourse within the academic community enhances collective understanding and fosters the development of innovative approaches in the field of time-synchronization method.

3.1.2. Selection Criteria for Algorithms

The selection of an appropriate time scale algorithm requires careful consideration of several critical factors that influence both its performance and applicability. Key

93 aspects include the specific requirements of the application domain, the nature of the data being processed, and the desired level of accuracy in time measurement. Equally important are the algorithm's computational complexity and efficiency, which determine its practical feasibility. Robustness and adaptability to varying conditions are essential to ensure reliability in diverse scenarios. Given the interplay of these factors, a
151 comprehensive evaluation is necessary to align the algorithm with the overall objectives of the project. In essence, the development of a time scale algorithm demands particular attention to accuracy, stability, and complexity [84].

41 In evaluating algorithm performance, accuracy refers to the ability of the algorithm to minimize discrepancies in time and frequency. This characteristic is critical, as it directly influences the reliability and applicability of the algorithm across diverse contexts. A high degree of accuracy ensures results that closely approximate true values, thereby reducing the likelihood of errors arising from delays or miscalculations in frequency estimation. Such precision is particularly vital in domains where timing and frequency are of central importance. Consequently, assessing the accuracy of an algorithm serves as a fundamental criterion for determining both its effectiveness and practical utility.

On the other hand, stability denotes the capacity of a system or process to consistently deliver reliable outcomes over extended periods. This attribute is essential across multiple fields, including engineering, economics, and environmental sciences, where sustained dependability is paramount. A stable system demonstrates resilience by maintaining performance despite internal variations or external disturbances, thereby preserving the integrity of results. In research and development, stability signifies methodological robustness and dependable data, ensuring that empirical findings remain valid and applicable over time.

There are many different aspects to the idea of complexity, especially when it comes to the computing power needed for a certain task or algorithm. This part is very important because it has a direct effect on how easy and effective it is to put into action. Another important thing to think about is how easy it is to put into practice. This has to do with how useful it is to use theoretical ideas in real life. To figure out how complicated a system or process is overall, it needs to have a good grasp of both the computational needs and the problems that come up when putting it into action. This kind of evaluation not only helps to choose the right methods, but it also helps to think ahead about problems that might come up during execution.

The BIPM and other organizations put a lot of weight on the ideas of stability and reproducibility in how they work. This focus is very important for making sure that measurements and standards are the same and work in all situations. On the other hand, the NIST takes a different approach, focusing on the importance of monitoring in real time and being able to handle noise interference. Because of this difference in priorities, each institution needs to come up with its own algorithmic strategies that fit its own goals and needs [85]. By focusing on different things, both organizations help to move measurement science and technology forward, but they do so in different ways. The BIPM's focus on stability and reproducibility makes international measurement standards more trustworthy. NIST's focus on real-time monitoring and noise resilience encourages new ways to measure things and use them. In the end, the different approaches these organizations take show how their missions and the different problems they want to solve in metrology and standards development are different.

3.2. Mathematical Modeling

To establish a reliable and stable timescale, the outputs of multiple atomic clocks must be combined into a composite system. This composite timescale serves as a critical reference at both national and institutional levels, underpinning numerous applications that demand high-precision timing. By providing a unified standard, it ensures consistency and accuracy across diverse domains. Integrating this timescale into various systems enhances synchronization and coordination, which are essential for technologies and methodologies that rely on precise temporal measurements. Beyond improving the reliability of timekeeping, the composite timescale drives advancements in fields where accurate timing is indispensable, thereby safeguarding the integrity of scientific and technological endeavors [86].

30 In contexts where accuracy is paramount, the establishment and maintenance of such a reference system are vital for achieving dependable outcomes. The principal aim

of this initiative is to systematically reduce discrepancies caused by individual clock errors while simultaneously enhancing long-term system reliability. This involves implementing strategies that not only correct existing measurement issues but also strengthen the system's resilience over time. By focusing on both error minimization and durability, the initiative seeks to create a robust framework for timekeeping mechanisms. Ultimately, this approach ensures sustained accuracy and consistency, enabling dependable application in high-precision environments and establishing an infrastructure capable of withstanding the challenges associated with temporal inaccuracies. The mathematical expression for a composite timescale is given by Eq. 3.1.

$$TA(t) = \Sigma\, w(i) * x(i) \qquad (3.1)$$

60 where x(i) is the reading of the i-th clock, w(i) is the weight associated with the i-th
18 clock, N is the total number of clocks in the ensemble, and TA(t) is the timescale output.

3.3. Timescale Realization Algorithms

180 Setting a timescale is an important step in time and frequency metrology, which is the science of combining the outputs of many atomic clocks to create a continuous, stable, and very accurate representation of time. Timeframe realization techniques are what make this process possible on a computer. They let different clock data be combined into a single, optimized timeframe. The goal of these algorithms is to keep the clock's performance stable over time, reduce noise, and keep the frequency stable over time. These methods rely heavily on statistical modelling, signal estimation, and optimization techniques. They often use weighting schemes based on the differences between individual clocks or predictive filtering models like Kalman filters. Because
159 metrology institutions around the world use different types of clocks, such as cesium beam standards and hydrogen masers, algorithms need to be very flexible. The method you choose has a direct effect on the timescale's durability, continuity, and ability to be traced back to UTC. Over the years, algorithmic complexity has grown to include things like real-time error estimates, outlier rejection, and drift correction [87]. This has made it possible for organizations like BIPM, NIST, and USNO to offer very accurate national timeframes.

3.3.1. Simple Average Algorithm

Each clock involved in the process is given equal weight by the averaging algorithm. This method eliminates any potential bias that might arise from the clocks' varying degrees of influence by ensuring that each clock contributes consistently to the final computed average. The algorithm's egalitarian approach guarantees a balanced representation of each clock's time data, which is essential for achieving a reliable and accurate average. Because it lessens the impact of outliers and encourages a more robust data aggregation, this technique is particularly beneficial in circumstances where clocks may show time inconsistencies. The simple average technique emphasizes the approach's simplicity and serves as a fundamental method in time synchronization work. **S**imple average algorithm weight can be assigned using Eq. 3.2.

$$wi = \frac{1}{\mathrm{N}} \quad \forall i \qquad (3.2)$$

The method's low computing cost and straightforward implementation process set it apart. Because of this feature, it is particularly advantageous in circumstances where resource efficiency is crucial. The implementation's simplicity makes it more appealing and allows for greater accessibility and use in a variety of fields. As a result, in settings with limited computational resources, this approach not only increases usability but also encourages adoption. The characteristics of this approach make it a viable option for practitioners and scholars looking for effective solutions with low overhead. The method's potential for broad applicability in a variety of scenarios is highlighted by the beneficial balance between computing efficiency and user-friendliness. It is important to understand that this system is extremely vulnerable to broken or inoperable timepieces. For the system to function at its peak, time measurements must be accurate and dependable. Any changes or issues with the clock systems could have serious repercussions and could jeopardize the overall reliability and effectiveness of operations that depend on precise timing. Therefore, it is essential to keep the clocks in optimal condition to avoid any unfavorable outcomes from their degradation or malfunction. This vulnerability emphasizes how strict monitoring and maintenance procedures are required to maintain the operational standards that are necessary for efficacy. This method is inappropriate for applications needing high accuracy since the integrity of the timeframe can be seriously compromised by the failure of a single clock. The timing mechanism's dependability is crucial in scenarios where accuracy is required; any change or issue in one part can have cascading effects that jeopardize overall performance. Reliance on such a system might not meet the exacting requirements needed for contemporary technical applications. Given that even minor deviations can result in significant operational challenges, this emphasizes the need for robust design and redundancy in systems where time is of the essence. Therefore, it is essential to investigate other approaches that ensure improved reliability and accuracy in timekeeping devices, particularly in fields where exact timing is essential for operation and success.

3.3.2. Weighted Average Algorithm

The weighted average technique represents a significant improvement over the conventional simple average method. In this system, the significance of the various clocks is determined by their performance. This accounts for the reliability and precision of each timepiece, thereby enhancing the data's nuance and accuracy. The weighted average provides a comprehensive representation of the data by assigning a greater weight to certain performance indicators than to others. This enhances the analysis's overall rigor. This approach not only enhances our comprehension of the evolution of performance over time, but it also underscores the significance of considering performance variability during the evaluation process. Therefore, the weighted average method is a superior analytical instrument, as it enables individuals to make more informed decisions and provides them with insights that are more consistent with the actual performance of the clocks [88].

Different organizations use different methods to figure out variances. For example, the BIPM uses a traditional statistical method to figure out variance. This method is based on traditional statistical ideas that help us understand how data points are spread out in a dataset. The way one calculates variance can have a big impact on how one understands data and the conclusions one draws from statistical analyses. Because of this, researchers and practitioners must be aware of the specific methods used by different institutions, as these can result in different conclusions and results in the field of statistical analysis. The BIPM's use of classical statistical variance shows how important it is to use tried-and-true methods to make sure that things stay the same and the BIPM ALGOS timescale Eq. 3.3.

$$w_{i(t)} = \frac{\left\{\left(\frac{1}{\sigma_i^2}\right)\right\}}{\left\{\sum_{j=1}^{n}\left(\frac{1}{\sigma_j^2}\right)\right\}} \quad (3.3)$$

where, $w_{i(t)}$ is the weight assigned to the i-th clock at time t,and σ_i^2 is the variance associated with the i-th clock. The National Institute of Standards and Technology (NIST) uses the method of using squared prediction errors in its analyses. This method is an important part of evaluating predictive models because it measures how different the predicted values are from the actual values. NIST makes the analysis more sensitive to larger errors by squaring them. This gives a stronger way to judge how accurate a model is. The Allan variance is a statistical tool that the United States Naval Observatory (USNO) uses to look at how stable frequency standards are. This method is very useful in many areas. This method works especially well for checking how well oscillators and clocks work over different time periods. Researchers can use Allan variance to measure how much the frequency changes and find possible sources of noise that could affect the accuracy of timekeeping devices. This analytical method is necessary to make sure that the results are reliable and this method systematically reduces the negative effects of clocks that don't work well, which helps improve stability in both the short and long term. Using this method, one can effectively deal with the problems caused by clocks that don't work well, which is important for keeping many systems safe and reliable. This method is dynamic, so it can be changed in real time to make sure that performance changes are quickly dealt with. This makes the system much more stable overall, which leads to results that are more consistent and reliable. The method's full effectiveness in improving performance metrics and making sure operations can keep going is shown by its dual focus on short-term and long-term stability. In fields where accuracy and dependability are very important, these kinds of improvements are necessary. This shows how important it is to keep improving technological methods. A significant improvement over the simple average is the weighted average approach**,** where clocks are weighted according to their performance and the weight can be derived using Eq. 3.2 to given Eq. 3.4.

$$w_{i(t)} = \frac{1}{\left\{\left\{\sigma_i^{2(t)}\right\}\right\}} / \left\{\sum_j \{1/\sigma_j^{2(t)}\ \}\right\} \quad (3.4)$$

where w is the weight associated with the clock "i", σ is the variance associated with the clock "i".

3.3.3. Kalman Filtering-Based Approaches

The Kalman filter is a very advanced and flexible way to make time scales. This method uses a structured way to figure out the state of a dynamic system based on a set of measurements that are not complete and have noise. The Kalman filter improves its predictions over time by combining prior knowledge with new data. This makes time scale generation more accurate. It can be used in many fields, such as engineering, economics, and robotics, where accurate time measurements are important for making good decisions and getting the best results. The Kalman filter's underlying mathematical framework makes it even more important for modern data analysis and system modelling. The system works very well because it uses predictive algorithms that help it accurately predict and fix clock states. This is done through a series of recursive updates that make the time measurements more accurate and reliable [89]. This method not only makes operations run more smoothly, but it also makes sure that the system stays in sync with the least number of errors. The use of these advanced methods together shows how important iterative processes are for getting better performance metrics in timekeeping technologies. It is clear that these filters are used in the National Institute of Standards and Technology (NIST) Temps Atomique (TA) and the Atomic Time 1 (AT1) framework, where they play important roles. In particular, these filters are used for real-time correction, which improves the accuracy and dependability of data processing. Also, using them makes the systems they are a part of stronger overall, which means that performance stays the same even when conditions change. The fact that these filters can do two things at once shows how important they are in modern technology [90].

The KAS-1 and KAS-2 systems have advanced features that make them more useful in the field. One of the most important features of these systems is noise modelling, which lets you accurately represent and control noise within the signal processing framework. They also offer frequency ageing compensation, which is very important because it deals with how frequency response changes over time. These improvements make the systems much more reliable and perform better overall, making them suitable for many applications where accuracy and stability are very important [91].

The addition of these features shows a dedication to improving technological solutions in this area.

3.4. Simulation Framework

To effectively evaluate algorithmic performance, a comprehensive simulation framework is required. In this study, simulations are conducted using a dual approach that incorporates both synthetic datasets and real-world clock datasets, enabling a thorough assessment of algorithm reliability under diverse conditions. The framework consists of two principal components. First, a clock ensemble simulation is performed using known noise parameters, allowing analysis of ensemble behavior under specific noise conditions. Second, data sampling is implemented in two forms: periodic sampling, where measurements are taken at fixed intervals to ensure consistency, and aperiodic sampling, where data are collected at irregular intervals determined by events or conditions. Together, these components provide a complete representation of system behavior and performance, offering insights into the interaction of clock ensembles and the influence of noise.

Within this framework, different algorithmic modules, such as the simple average, weighted average, and Kalman filter, are employed for data analysis and signal processing. The simple average provides a basic measure of central tendency, while the weighted average incorporates varying importance across data points for more refined
37 analysis. The Kalman filter, in contrast, offers an advanced technique for estimating the state of dynamic systems from noisy and incomplete measurements. Each of these methods contributes to improving the accuracy and robustness of data interpretation in both theoretical and applied contexts. Computational tools such as MATLAB and Python are widely utilized to implement these algorithms, as they provide efficient platforms for simulation, modeling, and analysis. Furthermore, real-world datasets sourced from NMI logs are integrated into the framework, ensuring empirical validity and enhancing the depth of evaluation.

3.5. Performance Metrics

The evaluation of timescale algorithms requires the use of specific performance metrics that quantify accuracy, stability, and reliability. One of the most widely employed measures is the Allan Deviation (ADEV), which characterizes frequency stability over varying averaging periods. By examining ADEV, researchers gain insight into the robustness of timescale algorithms under different operating conditions. Since frequency stability directly influences the accuracy of timekeeping devices, ADEV serves as a fundamental tool for identifying algorithmic weaknesses and guiding optimization in both design and implementation. Its role underscores the central importance of stability analysis in advancing timekeeping technologies across diverse scientific and engineering domains.

A second critical metric is Time Error (TE), which measures the cumulative deviation between a generated timescale and a defined reference. TE is particularly important in applications requiring precise synchronization, such as telecommunications, navigation, and scientific experimentation. By analysing long-term offsets, researchers can detect systematic departures and implement corrective strategies. Accurate measurement of TE ensures both temporal consistency and operational reliability, thereby maintaining system synchronization across sensitive applications.

Another essential consideration is frequency drift, which reflects gradual, long-term changes in frequency measurements. Drift often arises from environmental variations, equipment degradation, or process inconsistencies, and has significant implications in fields where frequency stability is paramount, particularly telecommunications and signal processing. In addition to these core metrics, supplementary indicators such as Prediction Error and TDEVprovide deeper insights. TDEV captures variations over extended periods, offering valuable information for evaluating filtering-based approaches and long-term prediction models. Similarly, Prediction Error assesses the accuracy and robustness of forecasted time values, strengthening the overall evaluation framework. Together, these measures establish a comprehensive methodology for assessing timescale algorithms, ensuring both theoretical rigor and practical applicability. Far from being auxiliary, these metrics form an integral part of a robust analytical process, enabling more reliable predictive modelling, enhanced filtering techniques, and improved system resilience.

Key performance metrics used to evaluate timescale algorithms include ADEV, *i.e.*, to evaluate frequency stability over varying averaging times, TE**,** i.e., it measures cumulative offset between the generated timescale and a reference and frequency drift: Captures long-term deviations in frequency. Additional metrics such as TDEV and Prediction Error are also considered, particularly for filtering-based approaches.

3.6. Comparative Results and Discussion

This section presents a comparative evaluation of seven prominent timescale algorithms implemented by major NMIs, namely, USNO A.1, BIPM ALGOS, NRL KAS-1, TSC KAS-2, NIST AT1, NIST TA, UTC(NRC). The United States Naval Observatory (USNO) A.1 employs a weighted average method designed to prioritise frequency stability over extended periods. This approach is crucial for ensuring the consistency and reliability of the observatory's timekeeping standards. The USNO A.1 utilises a weighted average method to effectively minimize variations that could potentially affect the precision of time measurement. The emphasis on stability is crucial; the Allan variance serves as an important metric for assessing clock stability, demonstrating its utility in tracking temporal performance across extended periods. This statistical method is crucial for assessing the frequency stability of oscillators, particularly within timekeeping systems. The Allan variance provides a comprehensive analysis of frequency variations over time, elucidating the essential noise mechanisms that affect clock performance. The Eq. 3.5 was used.

$$w_i = \frac{\left\{\left(\frac{1}{AVAR_i^2}\right)\right\}}{\Sigma_j\left(\frac{1}{AVAR_j^2}\right)} \qquad (3.5)$$

where, w_i is the normalized weight assigned to the i-th clock, and $AVAR_i^2$ is the squared Allan variance of the i-th clock. The inherent simplicity of the system indicates its inadequacy in managing clock conflicts. The limitation arises from the lack of sophisticated methods for modelling noise and effectively eliminating outliers, both of which are critical in the analysis of temporal data. The absence of these advanced procedures may hinder the overall performance of the system in contexts where precision and accuracy are essential. While the system's simplicity offers specific advantages, it simultaneously restricts its ability to tackle more complex challenges associated with timekeeping and data integrity. This indicates limitations in its capacity to respond to alterations within the dynamic system, thereby hindering its overall adaptability.

The BIPM employs a conventional weighted mean approach as the main method for determining UTC on a global scale. This method is crucial for ensuring accuracy and uniformity in timekeeping across various regions, facilitating global synchronization in time measurement. The BIPM enhances the reliability of the UTC standard by employing a weighted mean to integrate temporal data from various atomic clocks worldwide. This approach evaluates the precision of each time source and amalgamates their inputs into the comprehensive timekeeping framework, ensuring that the resultant UTC offers a complete and fair depiction of international time standards. This traditional methodology underscores the importance of rigorous scientific methods in establishing and maintaining a universally accepted time standard, essential for various applications such as navigation and telecommunications. The operation of clock ensembles is regulated by a set of stringent standards that outline the norms and procedures to be followed. The data submission process from the participating National Metrology Institutes (NMIs) is governed by established regulations. The regulations are essential for maintaining the integrity, accuracy, and reliability of timekeeping systems, while also ensuring a standardized approach to data collection and reporting across different entities is given by Eq. 3.6.

$$w_{i(t)} = \frac{\left\{\left(\frac{1}{\sigma_i^2}\right)\right\}}{\left\{\sum_{j=1}^{n}\left(\frac{1}{\sigma_j^2}\right)\right\}} \qquad (3.6)$$

where $w_{i(t)}$ is the weight assigned to the *i*-th clock at time *t*, σ_i^2 is the variance associated with the i-th clock. Although the methodology does not incorporate real-time adjustments or noise modelling, it demonstrates a significant degree of standardization. Additionally, it ensures exceptional long-term consistency and maintains traceability to the

International System of Units (SI) second. This attribute is significant as it underscores the reliability and consistency of the measurements obtained through this method. Standardization is crucial in various scientific and technological fields, where precision and accuracy are of utmost importance. The consistent nature of the data indicates that the approach can produce reliable conclusions over extended periods, which is essential for longitudinal studies and applications requiring robust reference points. The traceability to the SI second highlights the method's alignment with internationally recognized standards, thereby enhancing its credibility and applicability in various contexts. Despite certain limitations in dynamic attributes, the method's benefits in standardization, uniformity, and traceability render it an essential tool for obtaining accurate and reliable measurements. The primary objective of this program is to ensure that all international contributors follow a consistent approach in their donations. The emphasis on consistency takes precedence over the need for flexibility in real-time interactions. The program aims to establish a coherent framework that emphasizes consistency, thereby enhancing collaboration among diverse contributors and improving the overall effectiveness of collective efforts. A standardized approach is crucial for fostering a reliable environment where all participants can engage meaningfully, ensuring that their contributions align with established standards and expectations. The pursuit of consistency serves as a crucial element that underpins the collaborative process, leading to enhanced outcomes and a stronger collective impact. Prioritizing consistency over flexibility represents a strategic choice aimed at improving collaborative interactions among international participants, thus reinforcing the integrity and coherence of the overall project. This approach enhances contributions while minimizing disputes arising from varying interpretations or applications of the established criteria. The initiative's commitment to ensuring consistency among international contributors represents a strategic effort to enhance collaboration and attain more effective results, with real-time adaptability being a secondary focus relative to this main goal.

The NRL KAS-1 represents a significant advancement in the complexity associated with algorithmic comprehension. This development marks an important point in the evolution of algorithmic design and implementation, as it introduces a level of complexity that challenges traditional frameworks of understanding. This innovation has important implications, necessitating a re-evaluation of the understanding and application of algorithms in various domains. The intricate features of the NRL KAS-1 underscore the necessity for enhanced methods in algorithmic analysis and interpretation, fostering a deeper comprehension of the essential principles governing algorithmic functionality. In navigating this new environment, it is crucial to cultivate a deeper comprehension of the mechanisms at play, thereby equipping stakeholders to address the complexities inherent in these advanced systems. This evolution highlights the growing complexity of algorithmic frameworks and emphasizes the need for interdisciplinary collaboration to improve clarity and understanding. The system operates on a Kalman filtering architecture, serving as a foundational framework for its functionality. This architecture facilitates the integration of various processes through the use of targeted weighting algorithms tailored for short-term, medium-term, and long-term stability intervals. The system utilizes different weighting strategies to enhance performance across various temporal scales, thereby increasing its overall effectiveness and reliability in dynamic contexts. The system exhibits significant capability in noise modelling, facilitating precise real-time state estimation and effective drift correction. The combination of these attributes improves precision and reliability, ensuring optimal system performance across various environments. The use of advanced noise modelling techniques helps minimize disruptions that could compromise the integrity of processed data. Furthermore, real-time state estimation enables continuous monitoring and adjustment of system parameters, enhancing responsiveness to environmental changes. The implementation of drift correction techniques is crucial, as it reduces measurement variations over time, thus maintaining the accuracy of the system. The system's features underscore its ability to deliver consistent and dependable performance, making it a vital instrument in scenarios where accuracy is paramount. This solution is effectively structured for critical applications that necessitate continuous enhancement and can adeptly manage faults. Adaptability and evolution are essential in software development and system design, particularly for applications that carry out critical functions across various industries. The changing technological environment requires these applications to maintain high performance levels while incorporating mechanisms for error detection and correction. The implementation of a robust solution in this context ensures that the application can withstand unforeseen challenges and operational disruptions. Continuous improvement is fundamental to the development lifecycle, enabling the integration of user feedback, technological advancements, and established best practices. This iterative process enhances the application's performance and strengthens its resilience against potential failures. Moreover, the capacity to address errors is crucial for maintaining the program's integrity and reliability. A well-constructed system incorporates comprehensive error handling mechanisms that can identify, log, and address errors in real-time. This is as shown in the Eq 3.7.

$$TA(t) = \sum\left[w_{s(i)} * x_{s(i)} + w_{m(i)} * x_{m(i)} + w_{l(i)} * x_{l(i)}\right] \quad (3.7)$$

where, $w_s(i)$ weight for the short-term clock input $x_s(t)$, $w_m(i)$ is the weight for the medium-term clock input $x_m(t)$, and $w_l(i)$ is the weight for the long-term clock input $x_l(t)$.

The TSC KAS-2 represents a significant advancement compared to its predecessor, KAS-1, by enhancing the range of data processing methods available. This improvement is particularly evident in clock measurements that exhibit irregularities or occur at unusual intervals. Adapting to variability in data collection is crucial for ensuring accurate and reliable analysis, which facilitates a deeper understanding of the underlying phenomena. Advancements in TSC KAS-2 improve the processing capabilities of large data sets and reinforce the measurement framework, facilitating more detailed interpretations and applications in various research domains. TSC KAS-2 sets a new standard in data processing by addressing the challenges of inconsistent clock readings, thereby supporting future research and development initiatives focused on enhancing analytical capabilities. The current model is similar to its predecessor, particularly in its use of Kalman filtering techniques alongside various advanced methods for noise estimation. The efficacy of the model is significantly enhanced through these approaches, leading to greater precision and reliability in data processing. The incorporation of Kalman filtering is essential, facilitating the effective management of uncertainties present in the data. The implementation of advanced design in this system exhibits a significant degree of adaptability, particularly in situations characterized by irregular sampling or operational constraints. Despite these challenges, the system maintains a notable level of stability and durability over time, ensuring its effectiveness and reliability across various applications.

The NIST AT1 framework presents a novel concept of dynamic adaptation, which is fundamentally grounded in the utilization of prediction error variance as a criterion for establishing appropriate weighting. This approach signifies a departure from traditional static models, facilitating a more flexible and responsive system that can address variable fluctuations and uncertainties inherent in prediction processes. Equations for this algorithm is given as Eq 3.8, 3.9, and 3.10.

142 $$x_k = F * x_{\{k-1\}} + u_k \quad (3.8)$$

$$z_k = H * x_k + v_k \quad (3.9)$$

59 $$K_k = P_{\{k|k-1\}} * H^T * \left(H * P_{\{k|k-1\}} * H^T + R\right)^{-1} \qquad (3.10)$$

36 where, X_k-The state vector at time step k, F is the state transition matrix, $U_k$is the process
67 noise (usually assumed to be Gaussian with zero mean), Z_k is the observation (measurement) vector at time step k, H is the observation matrix, and K_k is the Kalman gain matrix at step k.

12 The framework aims to enhance the accuracy and reliability of forecasts through the use of prediction error variance, facilitating more informed decision-making in complex environments. This concept has significant applications across various domains where adaptive responses to fluctuating conditions are crucial. NIST AT1 contributes to the discussion regarding the importance of adaptability in predictive modelling and its potential to improve outcomes in real-world applications. This method enables the program to react to immediate fluctuations in the performance of the clock ensemble. The ability to adapt dynamically is crucial for maintaining optimal functionality and ensuring that the system aligns with the varying conditions of the clock ensemble. The algorithm enhances the efficiency and accuracy of the ensemble's operations via timely adjustments. The employed methodology incorporates robust mechanisms for identifying and rectifying outliers, thereby maintaining consistent accuracy in dynamic environments prone to fluctuations. The adaptability of this approach is crucial for maintaining the integrity of data analysis in contexts characterized by unpredictability and uncertainty. Efficiently addressing anomalies enhances the reliability of results and fortifies the overall resilience of the analytical framework. The significance of these properties is

paramount across various domains, where maintaining result consistency is essential, notwithstanding the inherent unpredictability of the data environment. The architecture of the system prioritizes accuracy and reliability, making it a crucial tool for researchers and professionals seeking to derive meaningful insights from complex datasets. The algorithm is well-known for its remarkable flexibility and responsiveness, attributes derived from its initial design and development approach. This temporal algorithm is notable for its ability to adapt to varying situations and requirements, enhancing its applicability across diverse contexts. The fundamental principles and methods employed in its creation significantly improve its efficacy. This approach diverges from the guidelines set forth by the NIST TA, which prioritizes adaptability within its operational frameworks. The Eq. 3.11of NIST-TA is,

$$w_{i(t)} = \frac{\left(\frac{1}{PE_i^2}\right)}{\Sigma_j\left(\frac{1}{PE_i^2}\right)} \qquad (3.11)$$

where, $w_i(t)$ is normalized weight assigned to the i-th clock at time t, PE_i is the predictionerror variance (or simply squared prediction error) of the i-th clock, and $\Sigma_j\left(\frac{1}{PE_i^2}\right)$ is the normalized sum of precisions across all clocks j.

The system is capable of processing inputs in both frequency and phase domains. It effectively manages datasets that may contain missing values or exhibit inconsistencies. While the fundamental weighting methodologies employed in this system may not exhibit the intricacy found in the AT1 or KAS series, it remains a respectable option for scenarios where configurability and versatility are more critical than achieving optimal stability. The inherent simplicity of its weighing algorithms enables straightforward deployment and adaptability in various settings, making it particularly suitable for environments that demand design and operational flexibility. Consequently, this system may sufficiently meet the needs of customers who value a wide range of applications, even though it may exhibit limitations in maximum stability under peak conditions. The balance between configurability and peak performance is essential when selecting appropriate systems for specific use cases, making this consideration a significant factor for those seeking to reconcile these opposing demands.

The system's straightforward weighing methodology, combined with its adaptability, presents a beneficial choice for clients in search of a reliable solution that can be tailored to diverse operational needs.

The National Research Council of Canada, UTC(NRC) serves as a crucial standard for time synchronization across various sectors, facilitating precise measurements and collaboration in both research and industry. The careful upkeep of this time standard reflects the Council's dedication to improving timekeeping practices and ensuring alignment with the evolving needs of both national and international communities. The National Research Council of Canada utilizes a modified Kalman filtering method designed for a particular category of high-performance timekeeping devices. This adaptation is crucial as it enhances the accuracy and reliability of clocks, ensuring that their operational characteristics are carefully calibrated to meet the demands of precise timing. The adjustment of the Kalman filter represents a substantial modification; incorporating moderate noise models and systematically excluding outliers markedly improves the stability of timekeeping systems [91]. This approach ensures precise time synchronization while maintaining the ability to revert to UTC. The integration of Global Positioning System (GPS) and Two-Way Satellite Time and Frequency Transfer (TWSTFT) enhances the reliability and accuracy of timekeeping systems. The integration of these approaches facilitates effective management of challenges associated with time distribution and synchronization, thereby improving the accuracy of temporal measurements in various applications [92].

This system, while not possessing the computational complexity of AT1 or KAS-1, achieves a commendable equilibrium of rapid response, consistent accuracy, and ease of use. The design facilitates effective interaction, allowing users to engage with the system successfully while maintaining a high degree of accuracy over extended periods. This equilibrium is crucial in various applications, where the necessity for swift reactions must be balanced with the need for reliable outcomes. The ease of use enhances its appeal, making it accessible to a broader audience and promoting its acceptance in various contexts. The inclusion of these characteristics underscores the system's practical significance, ensuring it meets the requirements of users seeking efficiency and reliability in their interactions. The integration of these elements positions the system as a practical option for individuals seeking an efficient and user-centered tool. This design choice reflects an understanding of the intricacies involved in developing technology that meets diverse needs while remaining accessible to users with different levels of skill. Moreover, formal comparisons utilizing Coordinated Universal Time (UTC) indicate that performance remains consistently accurate across various assessments. The uniformity is crucial for establishing a baseline in performance metrics, thereby enabling a standardized evaluation framework. The data derived from these comparisons is essential for evaluating the operational efficiency and reliability of the system in question. It exhibits reliable performance in official UTC comparisons. Table 3.1 shows the intercomparison of all these algorithms.

TABLE 3.1 TABULAR INTERCOMPARISON OF VARIOUS ALGORITHMS

Timescale Algorithm	Institution	Country	Algorithm Type	Key Features	Noise Mode-lling	Outlier Rejecti-on	Real-Time Capa-bility	Stability	Adapta-bility
USNO A.1	United States Naval Observatory (USNO)	USA	Weighted Average (Allan variance)	Conservative, stable design using Allan variance for weights	Partial (Allan-based)	Minimal	High	Moderate	Low
BIPM ALGOS	Bureau International des Poids et Mesures	France	Classical Weighted Average	International UTC contributor with strict ensemble control	None	Moderate	Moderate	High	Moderate
NRL KAS-1	Naval Research Laboratory (NRL)	USA	Kalman Filter	Multiscale weighting; dynamic prediction and drift compensation	Strong (state + noise)	Strong	High	Excellent	High
TSC KAS-2	Time Service Centre, Chinese Academy of Sciences	China	Advanced Kalman Filter	Enhanced KAS-1 with support for irregular input intervals	Strong	Strong	High	Excellent	High

Timescale Algorithm	Institution	Country	Algorithm Type	Key Features	Noise Mode-lling	Outlier Rejecti-on	Real-Time Capa-bility	Stability	Adapta-bility
NIST AT1	National Institute of Standards and Technology	USA	Weighted Prediction Filter	Real-time performance, prediction-error-based weights	Partial (prediction errors)	Strong	High	Very High	High
NIST TA	National Institute of Standards and Technology	USA	Composite Filter/ Weighted Average	Flexible, supports non-periodic and frequency-domain input	Partial	Moderate	Moderate	Good	Very High
UTC (NRC)	National Research Council (NRC)	Canada	Modified Kalman Filtering	Real-time UTC(NRC) generation with GNSS comparison and traceability	Moderate	Moderate	High	Very High	Moderate

3.6.1. Key Observations

The ability of both the KAS and NIST models to operate in real time represents a key differentiating feature between the two. This functionality allows for immediate processing and analysis, enhancing their applicability in various contexts. The real-time operation is crucial for scenarios requiring timely data interpretation and decision-making, thereby underscoring the importance of this characteristic in evaluating the effectiveness of each model. Understanding how each model leverages this capability can provide insights into their respective strengths and potential use cases. The distinction in real-time functionality is essential for users to consider when selecting a model that best fits their operational needs. The USNO A.1 algorithm is characterized by its conservative and predictable structure, distinguishing it from the BIPM ALGOS algorithm, which prioritizes standardization and simplicity [93]. The KAS-1 and KAS-2 systems incorporate advanced models, implement corrections for ageing, and exhibit improved statistical rigor when compared to previous iterations of the software. The National

81

Institute of Standards and Technology (NIST) has developed AT1 and TA to establish a balance between real-time effectiveness and reliability [94-95]. Table 3.2 gives the algorithm features of various institutions.

Table 3.2Algorithm Features of Various Institutions

Timescale	Institution	Algorithmic Features
USNO A-1	US Naval Observatory	Basic weighted average
BIPM ALGOS	BIPM	Classical variance, high standardization
KAS-1	Naval Research Lab	Multi-scale weighted Kalman filter
KAS-2	Time Service Centre	Enhanced Kalman filter, adaptive weights
NIST AT1	NIST	Frequency-domain Kalman filtering
NIST TA	NIST	Real-time adaptive weighted average

- ***Outlier rejection*** is robustly implemented in ***BIPM***, ***KAS-1***, and ***AT1***
- ***Kalman filtering*** is adopted in ***KAS-1***, ***KAS-2***, and ***NIST TA***, offering real-time adaptability
- ***Noise modeling*** is explicitly handled in ***KAS-1***, ***KAS-2***, and ***AT1***
- ***Real-time capabilities*** are a hallmark of ***KAS*** and ***NIST*** models
- ***Outlier rejection*** is robustly implemented in ***BIPM***, ***KAS-1***, and ***AT1***
- ***Kalman filtering*** is adopted in ***KAS-1***, ***KAS-2***, and ***NIST TA***, offering real-time adaptability
- ***Noise modeling*** is explicitly handled in ***KAS-1***, ***KAS-2***, and ***AT1***
- ***Real-time capabilities*** are a hallmark of ***KAS*** and ***NIST*** models

Table 3.3 shows the feature-wise comparison of algorithms.

TABLE 3.3 FEATURE-WISE COMPARISON OF ALGORITHMS

Feature	USNO	BIPM	KAS	NIST AT1	TA	NIST TA
Outlier Protection	NO	YES	YES	YES	NO	YES
Noise Modeling	NO	NO	YES	YES	NO	YES
Real-time Support	NO	NO	YES	YES	YES	YES
Multi-timescale Weighting	NO	NO	YES	NO	NO	NO

3.6.2. Trade-Offs

Each timeframe algorithm shows a different balance of trade-offs, just like the operational goals and technological infrastructure of the National Metrology Institute (NMI) that is running it. Kalman-filter-based models and other algorithms with a lot of complexity offer more flexibility and accuracy, but they also require a lot of computing power and advanced knowledge, which makes them hard to use in places with limited resources. Techniques that are optimised for real-time performance, like NIST AT1, can quickly adapt to changes in clock behaviour, but they may not be as stable in the long term as more conservative techniques like USNO A.1 or BIPM ALGOS. Also, achieving a high level of resilience, especially in outlier rejection and drift compensation, may require a lot of processing power and careful calibration, which may not be possible for companies that value simplicity and reliability. Each algorithm presents trade-offs in Complexity vs. Practicality, Real-time performance vs. Stability, and Robustness vs. Computational Load**.** These design choices are intentional and in line with each NMI's strategic goals, whether that means making it easier to generate UTC around the world, distribute time across the country, or run real-time operations smoothly.

3.7. Conclusion

This chapter explores the pivotal role of timescale systems in achieving precise timekeeping for applications such as telecommunications and global positioning systems. These systems depend on ensembles of atomic clocks and require the coordinated integration of clock networks, data acquisition units, algorithmic modules, and distribution mechanisms to ensure optimal accuracy and performance. Methodologies established by organizations such as the BIPM and NIST demonstrate the inherent complexity of timekeeping technologies and emphasize the need for algorithm selection based on criteria including accuracy, stability, and computational efficiency. Particular attention is given to the construction of composite timescales, developed through mathematical modelling approaches such as simple averaging, weighted averaging, and Kalman filtering, all of which contribute to enhanced precision. System performance is further evaluated using metrics such as Allan Deviation, Time Error, and Frequency Drift, which serve as indicators of stability and reliability. The continual evolution of timescale architectures highlights the growing importance of precise time in modern technologies. By advancing algorithms and methodologies, researchers can improve synchronization across a wide range of scientific and practical domains, thereby strengthening the foundations of contemporary metrology.

A comparative analysis of seven prominent timescale algorithms reveals the diverse approaches taken by different National Metrology Institutes (NMIs) to maintain accurate and reliable time. Each algorithm, including USNO A.1, BIPM ALGOS, NRL KAS-1, TSC KAS-2, NIST AT1, NIST TA, and UTC(NRC), presents unique advantages and limitations aligned with the strategic goals of their respective organizations. The chapter concludes that the selection of a timescale algorithm is contingent upon specific operational requirements, balancing flexibility, stability, and computational demands to identify the most suitable solution for various timekeeping and synchronization challenges.

This chapter investigates the critical role of timescale systems in achieving precise timekeeping for telecommunications and global navigation. It examines the integration of atomic clock networks, data collection units, algorithmic modules, and distribution systems to ensure optimal performance and accuracy. The chapter reviews methodologies developed by BIPM and NIST, highlighting the importance of algorithm selection based on accuracy, stability, and computational efficiency. Composite timescales, constructed using averages and Kalman filtering, are discussed alongside key performance metrics such as Allan Deviation, Time Error, and Frequency Drift. A comparative analysis of seven prominent algorithms demonstrates diverse approaches by National Metrology Institutes, emphasizing the need to balance operational requirements, stability, and flexibility for effective time synchronization.

Chapter 4

Data Collection and Methodology

Modern scientific and technical systems rely on accurate timekeeping, with national timescales providing a unified framework for synchronizing critical infrastructures and supporting Coordinated Universal Time (UTC). While the concept of timescale realization is universal, its implementation varies due to differences in atomic clocks, data acquisition, and computation methods. National timescales combine high-precision frequency standards, advanced preprocessing, statistical filtering, and machine learning to achieve optimal stability and accuracy, enabling robust performance across diverse scientific, technological, and practical applications.

4.1. Introduction

Modern scientific and technical systems depend on keeping track of time correctly. At the national level, time-scales offer a cohesive temporal framework that guarantees synchronization among essential infrastructures while supporting the global reference, UTC, overseen by the BIPM [95]. The notion of timescale realization is universal; yet, its implementation significantly differs among countries. This is due to the fact that each nation possesses its unique array of atomic clocks, data acquisition techniques, and computation methodologies. A national timescale is derived by the continual comparison and averaging of high-precision frequency standards such as hydrogen masers and cesium-beam clocks [96]. Achieving optimal stability and precision demands more than only dependable hardware. Advanced pre-processing, sophisticated statistical filtering, and increasingly, the application of machine learning is also required. This chapter delineates a comprehensive methodology for executing the national timescale, encompassing procedures for data collection, pre-processing, and model development that culminate in a robust system with enhanced performance and diverse applications.

4.1.1. Time Keeping Setup

46 The timekeeping setup consists of clock ensemble, data computation or timescale generation setup and time traceability setup as shown in the Fig.4.1. Number of clocks in the ensemble varies however most of the leading timekeeping laboratories have minimum

eight high performance clocks. The setup used for thesis work also consists of eight clocks. Here, two are AHM, one is PHM and rest five are Cs clocks to cover the varied range of clocks.

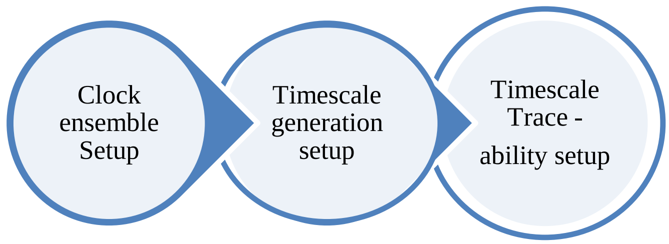

FIGURE 4.1 TIMEKEEPING SETUP AT NATIONAL TIMEKEEPING LABORATORY.

4.2. Data Collection and Nature of Clock Data

Hydrogen masers (both active and passive) and cesium-beam standards (Cs) are included in the time-scale configuration that was utilized for the investigation. Additionally, enhanced cesium variations were incorporated on a periodic basis. In the near term, hydrogen masers exhibit higher stability, but in the long run, they exhibit drift.
173 Cesium clocks, which are primary frequency standards produced from the hyperfine transition of the cesium-133 atom, provide timekeeping that is stable over an extended
160 period of time. The combination of short-term precision and long-term accuracy that the ensemble provides is a synergistic combination.

4.2.1 Data Acquisition

38 Almost every clock generates timing signals with a frequency of 5 MHz, 10 MHz and a one pulse per second, *i.e.* 1 PPS signal. This information was documented with
109 regard to an epoch that was based on a modified Julian day (MJD). The MJD is an uninterrupted enumeration of days (and their fractional components) employed in astronomy, geodesy, and timekeeping to facilitate the management of temporal measurements. The Julian Date (JD) measures the total days elapsed since January 1,
11 4713 BCE (Julian calendar) at 12:00 noon UTC. The Modified Julian Date (MJD) is delineated as MJD = JD - 2400000.5. This adjusts the initial epoch to November 17, 1858, at 00:00 UTC, hence reducing the numerical values for enhanced manageability.

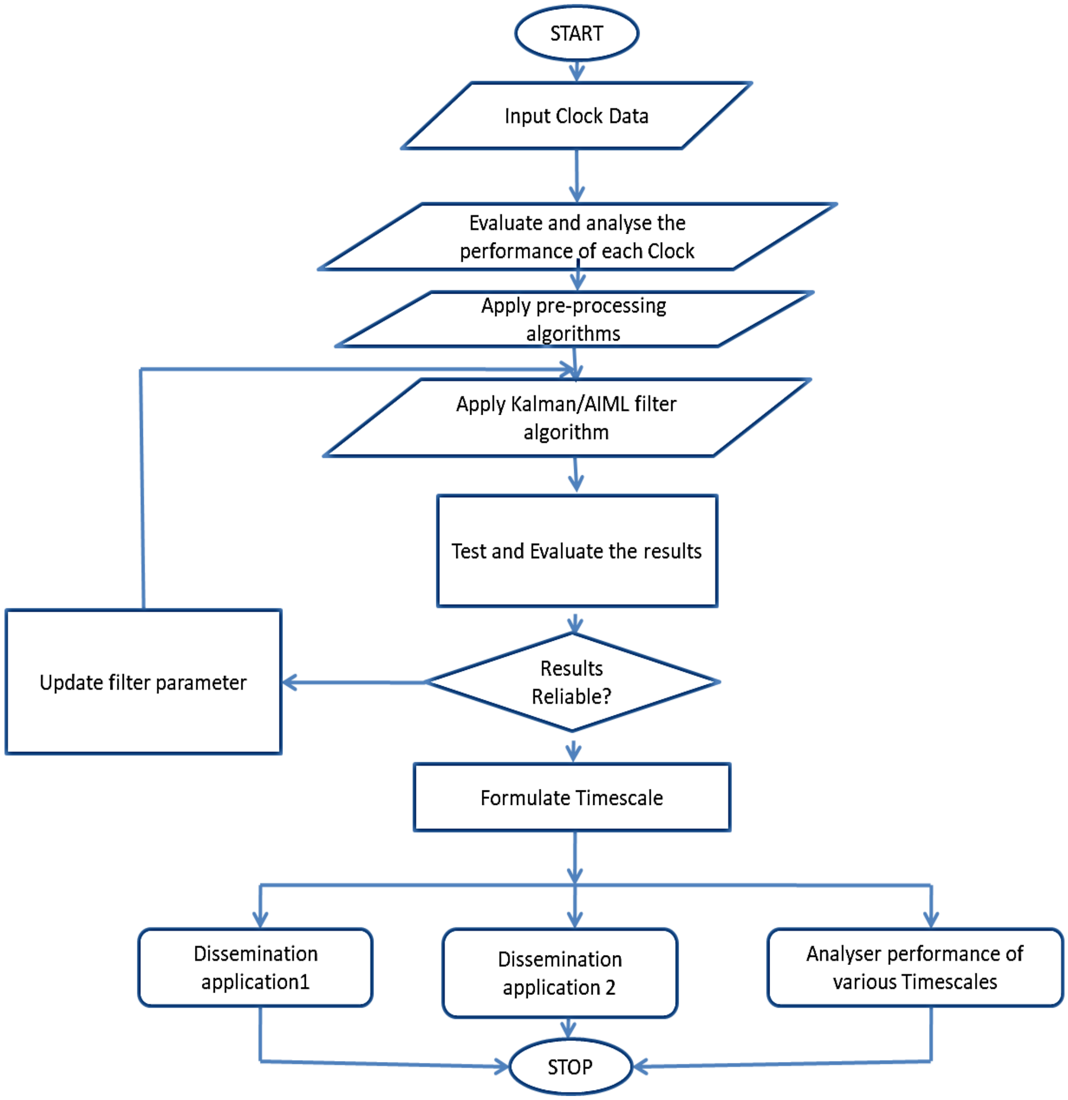

FIGURE 4.2 METHODOLOGY OF GENERATION OF AN EFFICIENT TIMESCALE

MJD is used in timekeeping because, it eliminates substantial constants in timing computations with an advantage of an uninterrupted tally of days, impervious to calendar anomalies. Complex structure of calendar day and date are extremely difficult to use in the timescale computation. MJD provided an easy and convenient way of logging of timing data. *e.g.* for January 1, 2000, 12:00 UTC, JD = 2,451,545.0 and MJD = 51,544.5. All clocks within the ensemble are continuously compared against the primary reference clock, denoted as UTC(k) for laboratory k, at regular intervals of thirty seconds. High-resolution outputs at the picosecond level are obtained using precision time-interval
34 counters and frequency counters. Timescale realization can be performed in either the
14 frequency or time domain; accordingly, both 1 PPS and 5/10 MHz signals are recorded.

In this thesis, the methodology focuses on timescale generation based on the 1 PPS signal. A robust dataset suitable for ensemble analysis was compiled through continuous monitoring over a two-year period. Given the possibility of anomalies within the collected data, early-stage pre-processing is essential to prevent potential complications [97]. Data pre-processing is therefore treated as an integral component of the timescale computation system. The complete methodology is illustrated in the flowchart shown in Fig. 4.2.

4.3 Development of preprocessing algorithms

The raw time difference data from the atomic clocks is often noisy and contains outliers due to various factors such as environmental disturbances, clock instabilities, and measurement errors. Pre-processing techniques are therefore essential to clean and smooth the data before it is used for timescale realization. After detailed evaluation of two-year-long data, it was found that this data contains some anomalies. impulsive outliers- due to single-point spikes from transient faults, time-tag anomalies resulting from missing/corrupt MJDs, causing misalignment sometimes, environmental drift due to gradual bias shifts from temperature/humidity, systematic discontinuities by maintenance or calibration, *etc*. These irregularities necessitated systematic preprocessing algorithms adaptation [98].

4.3.1 Comparison of various preprocessing algorithms

Various pre-processing techniques were analyzed before developing a pre-processing algorithm of timescale data [99]. These techniques include Time-tag repair through interpolation of missing MJDs, Uniform resampling to enforce evenly spaced time series, Mean Absolute Deviation (MAD) filter for robust outlier detection, Hampel filter for impulsive anomaly rejection and Savitzky-Golay filter for noise suppression while preserving trends as shown in Table 4.1.

4.3.1.1 Time-tag repair

Time-tag repair is employed to correct missing, corrupted, or mis-ordered timestamps within a dataset. In atomic clock ensembles, gaps or jitter in recorded offsets often arise from asynchronous sampling or data acquisition errors. Time-tag correction uses interpolation or standardized procedures to realign timestamps, ensuring continuity in the temporal index. Importantly, this process preserves the original measurement values and focuses solely on maintaining the structural integrity of the time series.

4.3.1.2 Uniform sampling

Uniform sampling resamples data onto regularly spaced intervals, hence regularizing measurement cadence. This is especially crucial when various clocks in an ensemble are not sampled concurrently. Interpolation techniques (*e.g.*, linear, spline) are employed to approximate absent data at consistent intervals. Although it enhances comparability among datasets and readies data for algorithms necessitating uniform spacing, it may also result in edge artefacts or interpolation inaccuracies.

4.3.1.3 Mean Absolute Deviation (MAD) filtration

MAD filtering is a resilient outlier detection technique founded on median absolute deviation. Each data point's deviation from the median is assessed using a scaled threshold ($k\sigma$). Due to its reduced sensitivity to extreme values compared to variance-based approaches, the Mean Absolute Deviation (MAD) is proficient at managing heavy-tailed distributions or global outliers over extended time periods. Nevertheless, its capacity to maintain delicate long-term patterns may be restricted when used with rolling windows.

4.3.1.4 Hampel filtering

Hampel filtering is a median-based sliding window method intended to mitigate impulsive anomalies or spikes [100]. For each point, the filter substitutes values that 155 exceed a specified threshold (e.g., k times the local standard deviation) with the local median. In contrast to basic clipping techniques, Hampel filtering adjusts locally and is exceptionally proficient at eliminating transient anomalies while preserving fundamental trends and oscillatory behaviors.

4.3.1.5 Savitzky-Golay filtration

The Savitzky–Golay filter is a polynomial smoothing method that applies low-degree polynomial fitting to consecutive data subsets through least squares optimization. In contrast to moving averages, it retains higher-order moments of the signal, including peak height and width, rendering it particularly appropriate for timekeeping data where long-term drift trends hold significance. It predominantly attenuates high-frequency noise while preserving signal integrity and temporal coherence.

TABLE 4.1COMPARISON OF VARIOUS PREPROCESSING TECHNIQUES.

Aspect	Time-tag repair	Uniform sampling	Hampel filtering	MAD filtering
Primary goal	Fix timestamps	Regularize cadence	Remove local outliers	Robust outlier detection
Operates on	Time index	Time + values	Values	Values
Noise reduction	None	Low–Moderate	Moderate (spiky)	Moderate (spiky/heavy-tailed)
Outlier handling	N/A	Poor (without prefilter)	Excellent (local)	Good–Excellent (global/rolling)
Signal/peak preservation	Excellent	Good (method-dependent)	Very good	Good
Trend preservation	Excellent	Good	Very good	Good
Edge behavior	N/A	Interpolation artifacts possible	Good	Good
Cost	Very low–Low	Low–Moderate	Moderate	Low–Moderate
Key params	Jitter/gap rules	Cadence, interpolation, anti-alias	Window, k sigma	k sigma, window (if rolling)

Although all five preprocessing procedures are crucial, their efficacy differs depending on the particular difficulties with atomic clock data. Time-tag repair and uniform sampling are essential for maintaining structural integrity but provide minimal benefits for noise reduction or anomaly mitigation. MAD filtering offers robustness against global outliers and heavy-tailed noise, but it is less appropriate for maintaining the modest stability characteristics of hydrogen masers and cesium standards due to its propensity to smooth over minute long-term drifts. Hampel filtering is proficient in locally removing impulsive outliers while preserving signal peaks and drift characteristics, rendering it particularly efficient against transient disturbances. Nonetheless, it does not directly mitigate background noise. The Savitzky–Golay filter addresses this gap by enhancing Hampel filtering through the smoothing of high-frequency variations while preserving the fundamental drift patterns. The most balanced approach, which provides both anomaly resilience and faithfulness to the long-term temporal dynamics that are essential for dependable timescale realization, is thus the combined Hampel + Savitzky–Golay pipeline.

4.3.2 Design of Proposed Pre-processing Algorithm

In the absence of a standardized preprocessing algorithm, multiple strategies were evaluated, with a two-step approach combining Hampel filtering and Savitzky-Golay smoothing demonstrating the highest effectiveness.

4.3.2.1 Hampel Filter Algorithm Implementation

The Hampel filter is used for outlier detection and correction in time series data,
127 such as clock measurements. It identifies and replaces anomalies by comparing each data
105 point with the median of its surrounding window. Algorithm of Hampel Filter is shown in figure 4.3.

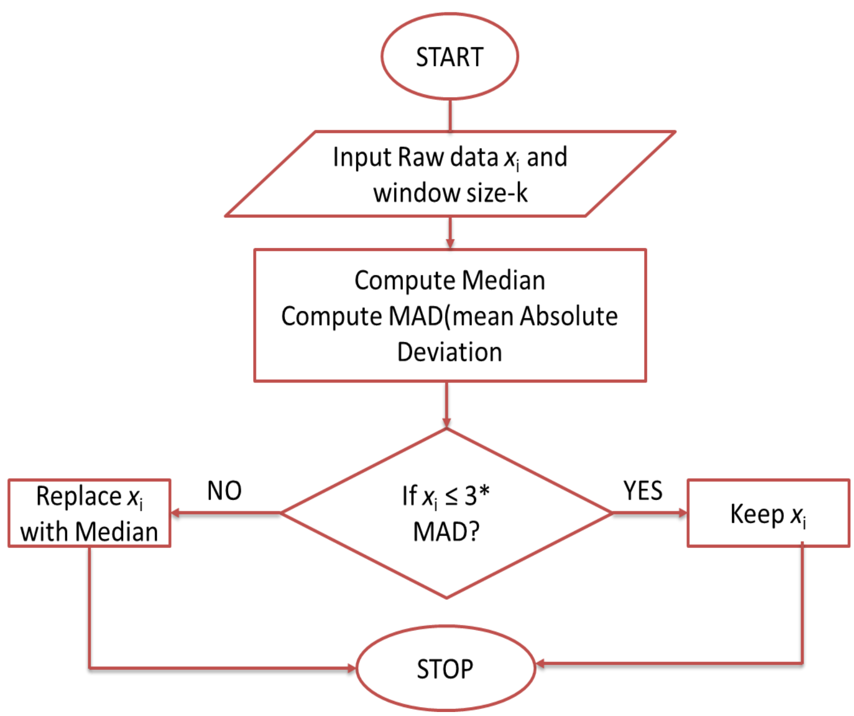

FIGURE 4.3 FLOWCHART OF HAMPEL FILTER

Let us assume a Data series as **X**={x1,x2,…,xn}.

Next step is the window definition around each point x_i , as

179 $$Wi = \{xi - k, \ldots, xi, \ldots, xi + k\} \qquad (4.1)$$

where 2k+1 is the total window size.

Next step is to compute Median of the window, which can be given as

$$\mathrm{Mi} = \mathrm{median(Wi)} \tag{4.2}$$

Hence, Computing Median Absolute Deviation (MAD) as

$$\mathrm{MADi} = \mathrm{median}(|\ \mathrm{xj} - \mathrm{Mi}\ |), \forall \mathrm{xj} \in \mathrm{Wi} \tag{4.3}$$

Next step is to check the Threshold condition for outlier detection, which is,

$$\mathrm{Ti} = \tau \cdot \mathrm{MADi} \tag{4.4}$$

where τ(tau) is a constant multiplier (typically 3).

Next step is to apply Outlier replacement rule as IF,

$$|\ \mathrm{xi} - \mathrm{Mi}\ | > \mathrm{Ti}, \text{then } \mathrm{xi} \leftarrow \mathrm{Mi} \tag{4.5}$$

4.3.2.2 Application outcome of Hampel Filtering on different Clock Data

Most of the outliers were found in Cs Clocks data. As shown in the results in Fig. 4.4, in CLOCK-02, the most outliers were found (759, ~2.20%). While maintaining the long-term drift pattern, the Hampel filter effectively detects and suppresses impulsive anomalies. Similarly, in CLOCK-09, the filter worked well to reduce the number of outliers (353, ~1.02%) without changing the drift trend. For CLOCK-08, we can say that a minimal number of outliers (32, approximately 0.09%) were found, suggesting a consistent performance. Filter impacts are negligible owing to the dataset's inherent cleanliness. For CLOCK-11, outliers identified (278, approximately 0.80%) have been effectively eliminated while preserving the consistent drift signal, similarly, for CLOCK-10, A limited number of outliers (93, approximately 0.27%) were effectively managed. Overall, the impulsive anomalies in caesium standards vary in intensity, with certain clocks (such CLOCK-02 and CLOCK-09) needing more stringent filtering. It was found that Hampel filtering enhances stability without altering patterns.

Hampel filtering was applied to AHM-01 and AHM-02, no outliers identified (0.00%), suggesting apt performance of clocks. The signals are unaffected by Hampel filtering, indicating inherent short-term stability. So overall, active hydrogen masers require little to no preprocessing and show remarkable resilience against impulsive disturbances. Same is the case with Passive Hydrogen Maser PHM-02, where no outliers identified (0.00%). The signal exhibits a continuous trajectory, underscoring the enhanced stability of passive H-masers. Hence passive H-masers preserve clean datasets, demonstrating their dependability as ensemble reference clocks. Refer Fig. 4.4 for the same.

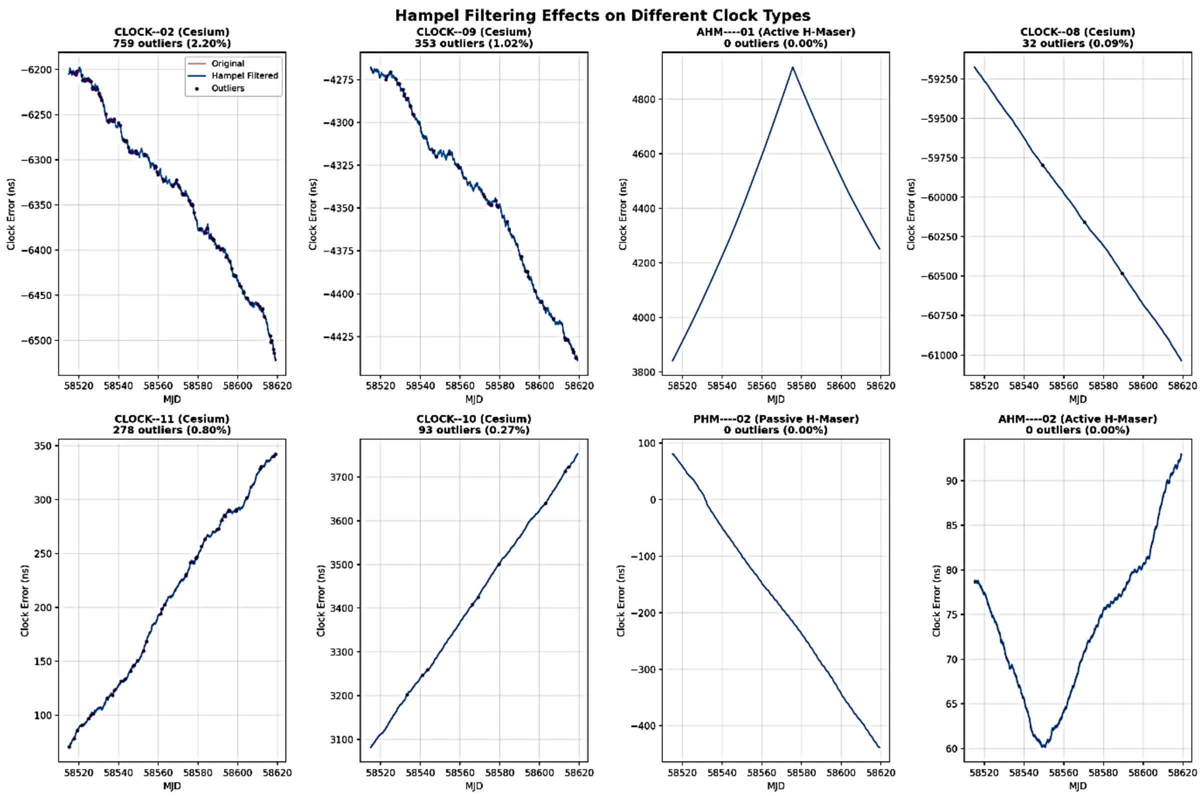

FIGURE 4.4 HAMPEL FILTERING IMPACT ON DIFFERENT TYPES OF CLOCK DATA- THE FILTER PRESERVED LONG-TERM DRIFT BEHAVIOUR WHILE IDENTIFYING AND ELIMINATING IMPULSIVE OUTLIERS, WHICH WERE MOSTLY SEEN IN CAESIUM CLOCKS (VARYING FROM 0.09% TO 2.20%). ON THE OTHER HAND, NEITHER THE ACTIVE NOR THE PASSIVE HYDROGEN MASERS SHOWED ANY OUTLIERS, WHICH SHOWS THAT THEY ARE MORE STABLE IN THE NEAR TERM AND DON'T NEED ANY PREPROCESSING.

A quantitative evaluation of the outlier distribution across various clock types and the efficacy of preprocessing is given by the data shown in Fig. 4.5. The main cause of anomalies was caesium standards; CLOCK-02 had the largest outlier fraction (2.2%), followed by CLOCK-09 (1.0%) and CLOCK-11 (0.8%), with minor contributions from other caesium units. Conversely, both active and passive hydrogen masers exhibited no outliers, highlighting their inherent stability. When compared to masers' clean performance, caesium clocks exhibit an average of 0.88% outliers, which is further supported by the aggregated study. The temporal analysis of CLOCK-02 indicated that outliers were dispersed across the measurement interval instead of being concentrated in particular episodes, implying persistent impulsive disruptions rather than singular occurrences. CLOCK-02's before-and-after comparison is significant because it shows how well Hampel filtering suppressed these anomalies while maintaining the underlying drift structure. This shows how important it is to preprocess caesium clocks in a specific way, while masers can be added to the group with little change

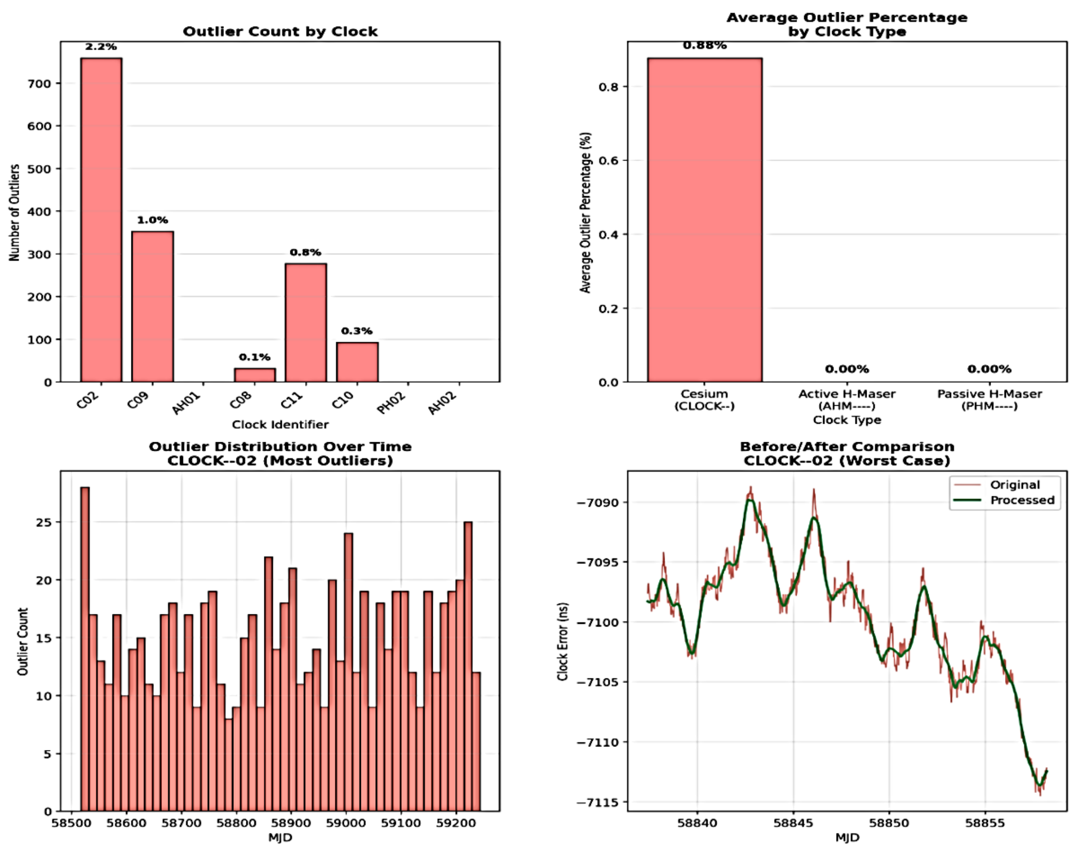

FIGURE 4.5 OUTLIER STATISTICS AND PREPROCESSING EFFECTS ACROSS CLOCK TYPES. CESIUM CLOCKS EXHIBITED THE MAJORITY OF ANOMALIES, WITH CLOCK-02 CONTRIBUTING THE HIGHEST FRACTION (2.2%), WHILE BOTH ACTIVE AND PASSIVE HYDROGEN MASERS SHOWED ZERO OUTLIERS.

4.3.2.3 Development of Savitzky–Golay algorithm

The Savitzky-Golay (Sav-Gol) filter is a widely used digital smoothing technique designed to preserve signal features such as peak shape and position while reducing high-frequency noise. Unlike simple moving average filters, Sav-Gol filtering fits a low-degree polynomial to a moving window of data via least-squares regression, making it particularly valuable for scientific and metrological applications where fidelity to the underlying signal is crucial. The steps involved in Sav-Gol filter implementation involves a Polynomial Fit. *i. e.*For a window of size n, the filter fits a polynomial of degree m

$$P(x) = a_0 + a_1 x + a_2 x^2 + \cdots + a_m x^m \qquad (4.6)$$

The polynomial coefficients are found by minimizing using Least Squares Minimization

$$minimize \sum_i =^{1\ n} \left(y_i - P(x_i)\right)^2 \qquad (4.7)$$

43 96 This can be expressed in matrix form as Ac=b, where A is a Vandermonde matrix constructed from window offsets, and c is the coefficient vector. The Matrix Form could be written ifA be the design (Vandermonde) matrix, **c** the coefficient vector, and b the data vector, then

$$A \cdot c = b \ (4.8)$$

Next step is to find the Least Squares Solution, which could be computed as

$$c = (A^t A)^{-1} A^t b (4.9)$$

So, the Convolution Form of Filtered Output could be given as

$$y_{filtered[i]} = \sum_j c_j \cdot y\left[i + j - {}^{W}/_{2}\right] \ (4.10)$$

where cj are precomputed convolution coefficients for the given window length and polynomial order.

So,design matrix entries are

$$A[j,k] = \left(j - {}^{W}/_{2}\right)^k \qquad (11) \quad for \quad j = 0 \ldots W, \quad k = 0 \ldots m$$

and the final smoothed value at center will be given as

$$y_{smooth[i]} = coeffs[0] \qquad (4.11)$$

On comparing Sav-Gol filter with other similar filters, it was found that, the 18 capacity of the Savitzky–Golay filter to successfully reduce noise while maintaining signal characteristics makes it stand out. This is crucial for the analysis of atomic clock data. In contrast to moving window averaging, which significantly attenuates noise while distorting peaks and trends, Savitzky-Golay smoothing preserves signal integrity and harmonic fidelity, hence safeguarding underlying drift fingerprints and periodic fluctuations in clock behaviour. In contrast to the Gaussian filter, which provides superior noise reduction but inadequate edge preservation and only moderate signal retention, the Savitzky-Golay approach offers a more favourable optimum by integrating effective noise suppression with intermediate edge handling proficiency. Although the median filter is good at removing outliers, it is not as good at preserving harmonics, which makes it less appropriate for scientific datasets that need to analyse subtle trends. Table 4.2 shows the Savitzky-Golay inter-comparison with other filters.

TABLE 4.2 SAV-GOL FITER INTERCOMPARISON

Method	Signal Preservation	Noise Reduction	Edge Handling	Computational Cost	Parameter Sensitivity	Harmonic Preservation	Use Case
Moving Window	Poor	Excellent	Poor	Very Low	Low	Poor	Simple Smoothing
Savitzky-Golay	Excellent	Good	Moderate	Low	Moderate	Good	Scientific Data
Gaussian Filter	Moderate	Excellent	Poor	Moderate	Good	Moderate	Image Processing
Median Filter	Good	Good	Good	Moderate	Low	Poor	Outlier Removal

Moreover, Sav-Gol filtering presents minimal computational expense and modest sensitivity to parameter selection, rendering it both efficient and dependable for long-term clock ensemble datasets. Crucially, its design is tailored for scientific data processing, where preserving the integrity of original signals, such as gradual frequency shifts or long-term stability indicators, is essential.

4.3.2.4 Application outcome of Hampel Filtering on different Clock Data

Application of Sav-Gol filtering was implemented on raw clock data. The results of the filtering on each clock are shown in Fig. 4.6. It was found that the filter works on all types of clocks, including caesium standards (such CLOCK-02, CLOCK-09, and CLOCK-11) and hydrogen masers (both active and passive). It eliminates all of high-frequency noise yet preserves the signal's overall path unchanged. The preprocessed curves (red) closely follow the trend of the original data (blue) without changing dramatic changes or long-term drifts. This keeps the genuine clock dynamics intact. The smoothing effect is important since it is mild and doesn't hide natural changes too much, while making long-term behaviors clearer. This shows that Sav-Gol filtering is a good step to take after Hampel. It helps with outlier removal by cleaning up the dataset and making it more stable for future modelling and time-frame realization.

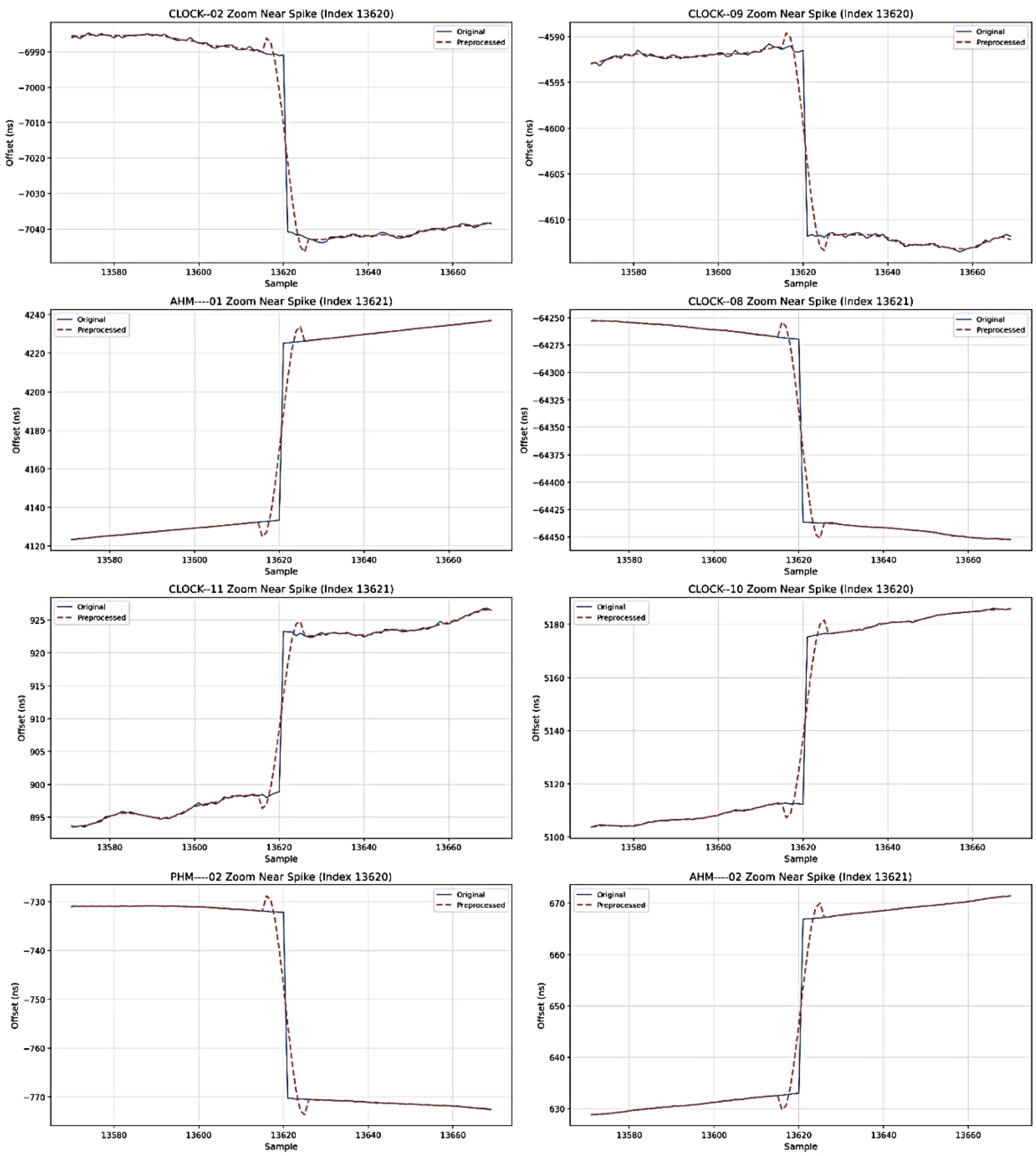

FIGURE 4.6 SAVITZKY–GOLAY SMOOTHING'S EFFECTS ON DIFFERENT TYPES OF CLOCKS CLOSE TO SHARP SPIKES. SHARP TRANSITIONS AND UNDERLYING DRIFT ARE PRESERVED WHILE HIGH-FREQUENCY NOISE IS REDUCED BY THE FILTER. THE PREPROCESSED SIGNALS CLOSELY RESEMBLE THE ORIGINAL DATA, DEMONSTRATING THAT SAV-GOL FILTERING IS A SUITABLE METHOD FOR IMPROVING CLOCK ERROR SERIES WITHOUT CHANGING INHERENT BEHAVIORS.

4.3.3 Results of pipelined pre-Processing

The pipeline method of applying Hampel first and tehn Sav-Gol proved to be the best strategy. The results of this two-step pre-processing algorithm can be seen in Fig. 4.7 and Fig. 4.8.

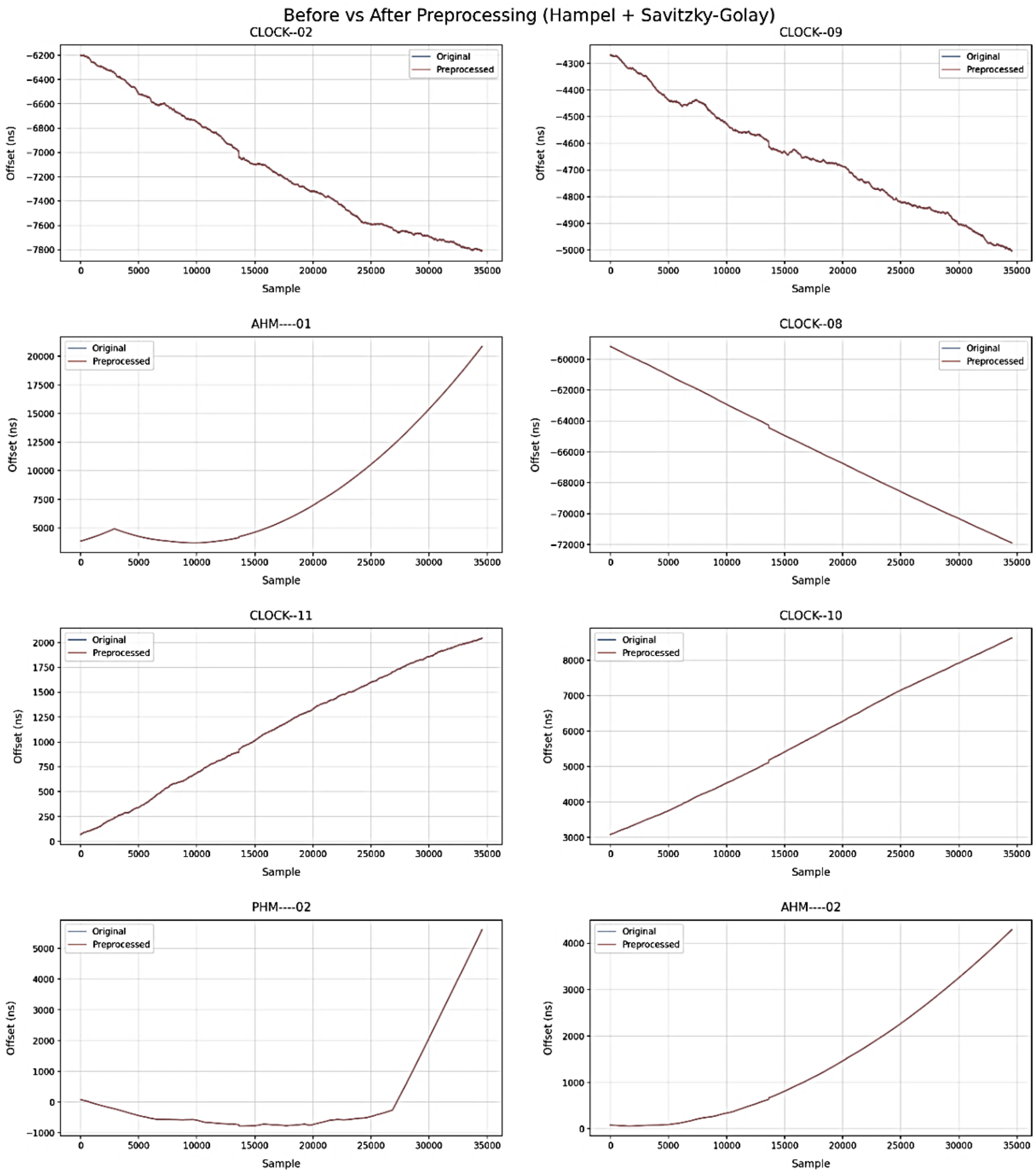

FIGURE 4.7 BEFORE AND AFTER PREPROCESSING USING THE HAMPEL + SAVITZKY–GOLAY PIPELINE ACROSS DIFFERENT CLOCK TYPES. THE COMBINED APPROACH EFFECTIVELY REMOVES IMPULSIVE OUTLIERS (VIA HAMPEL FILTERING) AND SUPPRESSES HIGH-FREQUENCY NOISE (VIA SAVITZKY–GOLAY SMOOTHING

The results presented validate the effectiveness of the hybrid Hampel + Savitzky–Golay preprocessing pipeline across all clock types. The approach proved effective for caesium clocks, successfully eliminating impulsive outliers and reducing high-frequency noise, all while maintaining the long-term drift characteristics that ensure their stability. The preprocessing for hydrogen masers, which exhibited minimal outliers, resulted in negligible changes, thus preserving their inherent short-term robustness. The close alignment between the original and preprocessed signals indicates that the integrated approach enhances the overall data quality while preserving the fundamental clock dynamics. The findings indicate that the hybrid pipeline serves as a balanced and dependable method for data preprocessing, allowing for the inclusion of both caesium and maser data in the timeframe ensemble with optimal accuracy.

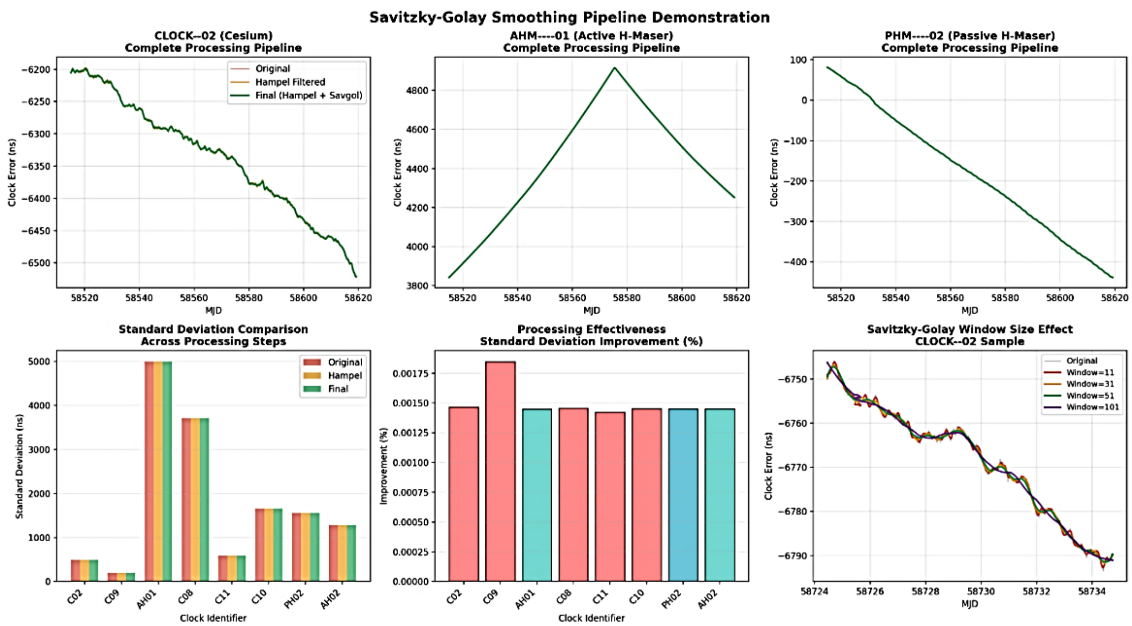

Figure 4.8 Demonstration of Two step filtering. The combined Hampel and Savitzky–Golay preprocessing reduces impulsive anomalies and noise in cesium clocks while leaving hydrogen masers largely unaffected, reflecting their intrinsic stability. Standard deviation comparisons and improvement metrics confirm significant gains for cesium units, while sensitivity analysis shows the method's robustness across different window sizes.

Fig. 4.8 reaffirms the efficacy of the comprehensive Hampel + Savitzky–Golay preprocessing pipeline for various clock types as well. The sequential application of Hampel filtering followed by Savitzky–Golay smoothing in caesium clocks like CLOCK-02 effectively mitigated impulsive anomalies and enhanced the signal, all while preserving the inherent drift trend. Active and passive hydrogen masers (*e.g.*, AHM-01 and PHM-02) exhibited minimal visual differences, indicating their inherent stability and affirming that the pipeline introduces negligible distortion, thereby rendering preprocessing unnecessary. The lower panels quantify these enhancements: the standard deviation comparison reveals a notable reduction in variance post-processing, especially for caesium clocks, while the percentage improvement plot demonstrates consistent gains throughout the ensemble. The sensitivity analysis of window size for Savitzky–Golay smoothing (CLOCK-02 sample) indicates that varying parameter selections produce consistent results, thereby affirming the method's robustness. The results collectively confirm the pipeline's effectiveness and stability for long-term implementation.

After preprocessing the individual clock data, it is now ready to form a timescale. Hence, as per methodology, these filtered clock data are combined to formulate an efficient timescale using various methods.

4.4 Development of Timescale Algorithm-Kalman Methodology

The primary aim in timescale realization is to integrate outputs from various atomic clocks into a singular, stable, and dependable reference. One of such widely trusted methodology is adopting Kalman filtering (KF) which acts as a recursive
158 estimating method that dynamically adjusts the weights of individual clocks based on their stability, thus reducing the influence of noisy or drifting units [101]. In cases characterized by non-linear behaviors, such as prolonged frequency drift, the framework
153 is augmented by the Extended Kalman Filter (EKF), which linearizes the system based on current estimates to address these complications [102]. The implementation involves several critical steps: first, system modelling of clock time and frequency evolution establishes the state-space framework; second, measurement equations are developed to connect observable clock offsets to fundamental state variables; and third, noise models are integrated to account for both intrinsic clock instabilities and instrumental uncertainties. The Kalman filter employs recursive estimation to continuously adjust the time-frame, ensuring resilience to anomalies while improving long-term accuracy [103].

The initial validation of the Kalman filter was conducted utilising GNSS-based
33 special formatted data known as CGGTTS (*Common GPS GLONASS Time Transfer*

20
85
165

Standard) format) data. These are special GNSS receivers used for timing applications. This CGGTTS format, not only includes difference between local clock and received GPS time with applied error correction to the data but also has other useful relevant parameters for further processing. The CGGTTS computation procedure is based on the analysis of measured pseudo-ranges for conventional 13-minute tracks. In this format the measurement data and measurement error associated with it is used to apply Kalman estimation. The results of the same are shown in Fig. 4.8.

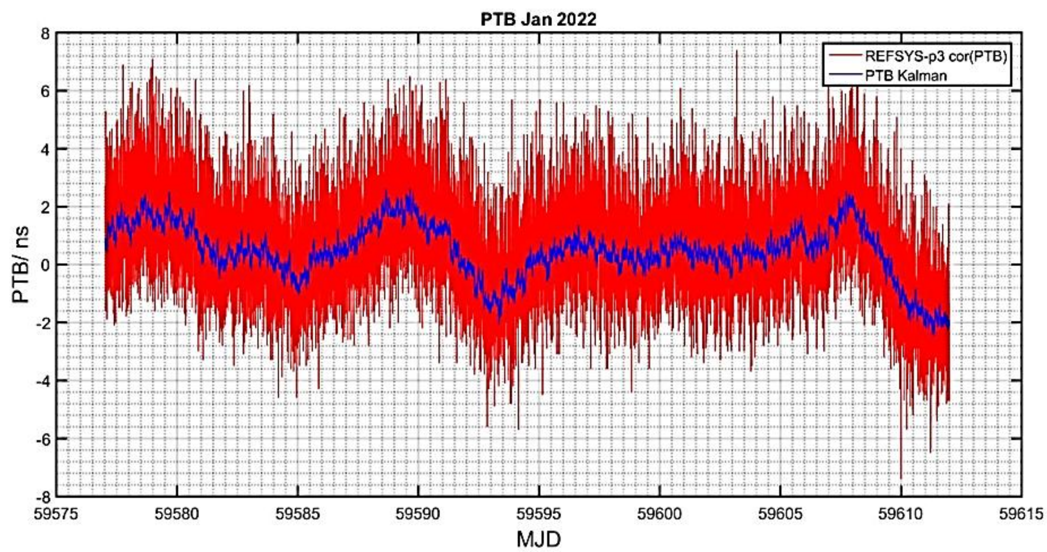

FIGURE 4.9 IMPROVEMENT IN PTB, GERMANY TIMESCALE FROM 8 NS TO 1 NS FOR 3 SIGMAS.

The ensemble constructed using traditional procedures exhibited stability with a 3σ uncertainty of approximately 8 ns, illustrating the efficacy of direct averaging of several clocks. The Kalman filter architecture enhanced temporal precision by adaptive weighting and recursive estimation, reducing 3σ uncertainty to 1 ns. The validating demonstrating its efficacy in significantly mitigating random noise present in the measurements [104]. While trying to adopt the method for timescale data, the measurement error values are not available. Hence first-order differences of the clock values were computed and these values served as proxy error estimates, which were subsequently utilized to calculate the Kalman gain in order to overcome the problem of missing measurement error data. In this step, separate clock outputs were systematically structured to create a composite timescale.

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4.5 Development of Timescale Algorithm-AI Methodology

AI/ML-based advanced modelling offers novel pathways for enhancing timescale realization beyond conventional filtering techniques [105].AI-driven anomaly detection models were adopted that facilitates the prompt identification of defective or errant clocks, averting the dissemination of mistakes into the timescale. To further improve precision, the methodology incorporated AI and machine learning (ML) models such as Support Vector Machines (SVM), Random Forests (RF), Autoregressive Integrated Moving Average (ARIMA), and hybrid models like Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [106-109]. Among these, the Random Forest weighted model demonstrated notable gains in stability and prediction accuracy over conventional techniques. ARIMA models were built by analyzing time series trends and seasonality in pre-processed clock statistics data. Model parameters were optimized using residual diagnostics to ensure accurate forecasting. ANFIS-based models were trained on 80% of the dataset and tested on the remaining 20%. The ANFIS approach proved highly effective in managing non-linearity and uncertainty, reducing RMSE by 25–30% compared to the Kalman filter baseline.

Methodology of machine learning, can forecast clock drift and stability, hence improving predictive accuracy in ensemble performance. Hence advance modelling of timescale is done by using these methodologies.

4.6 Methodology for Timescale Applications

After development of an efficient timescale, two real world applications were carried out. This section discussed the methodology of these case studies.

4.6.1. Case study 1- NTP via NKN-Provides synchronized time to Indian institutions and infrastructure

The All-in-View GNSS method was adopted for remote clock inter-comparison, owing to its superior synchronization accuracy on the order of nanoseconds. Unlike the Common View (CV) method, it utilizes all visible satellites simultaneously, thereby enhancing reliability and minimizing measurement uncertainty. The evaluated setup was established at the National Informatics Center (NIC), Hyderabad, India, where a Stratum-

1 NTP system was configured with a Rubidium frequency standard as the reference source, a GNSS receiver for satellite tracking, and an NTP server for network dissemination. Time differences between the satellite signals and ground station were measured, with system performance benchmarked against PTB, Germany, a recognized international timing authority, using official reference data obtained from the BIPM website.

4.6.2. Case study 2- Remote Calibration at Jantar Mantar

This work enables the preservation of heritage observatories while ensuring accurate temporal referencing. Sundials represent one of the earliest forms of timekeeping, relying on the movement of the Sun's shadow cast by a gnomon. The Jantar Mantar observatory in Jaipur, built by Maharaja Sawai Jai Singh II in the 18th century, houses the Vrihat Samrat Yantra, the world's largest gnomon sundial [110]. As part of bridging traditional and modern timekeeping, the objective of this study is to scientifically calibrate these heritage sundials with traceability to Indian Standard Time (IST). The adopted method utilizes remote calibration via NTP services, providing nanosecond-level accuracy and enabling alignment with modern atomic timescales. This approach ensures that the sundials remain not only cultural landmarks but also accurate instruments for researchers, horologists, and visitors, thus uniting historical ingenuity with present-day precision.

4.7 Methodologies for Validation Metrix

Following parameters adopted utilized the following parameter to evaluate the obtained results.

- **Allan Deviation (ADEV):** Benchmark for frequency stability over averaging time; lower values indicate higher stability
- **Time Deviation (TDEV):** Focuses on random fluctuations in the time domain
- **Comparisons with BIPM's UTC-UTC(NPLI):** Independent validation against global timescales
- Tools adopted- ORIGIN, STABLE 32, Python- analysis, MATLAB and Excel

This chapter investigates the data collection and methodology adopted to develop an efficient timescale. It covers the various methods adopted for pre-processing of the data. The various algorithms for pre-processing were evaluated and compared and found that Sav-Gol algorithms is best suited for the pre-processing of the clock data. This chapter also covered methodologies for development of efficient algorithms for example kalman filtering, AIML Algorithms and methodologies. The evaluation metrics and tools adopted to develop the algorithms were presented in the chapter.

Chapter 5

Development of Kalman Filter-Based Timescale Algorithm

This chapter explains the Kalman filter's application to timing clock data, including model formulation, state-space modelling, parameter estimation, and filter optimization. It also discusses linear vs. extended Kalman filters and presents initial validation using GNSS data to create an effective timescale. Covariance tuning and filter gain optimization are also covered

5.1. Introduction

The Kalman filter is a recursive mathematical algorithm used for estimating the state of dynamic systems in the presence of noise and uncertainties. Widely applied in navigation, control systems, and timekeeping, it combines predictions from a system model with real-time measurements to produce optimal estimates. By minimizing error covariance, the Kalman filter enhances stability, accuracy, and reliability, making it a fundamental tool for precise timescale generation and dynamic signal processing.

5.1.1. Historical Background in Time Metrology

It has been widely acknowledged that the Kalman Filter (KF) is an essential component of statistical estimation ever since it was first presented by Rudolf E. Kalman in the year 1960. Time and frequency metrology gradually adopted it after its early use in aircraft navigation, especially for enhancing clock ensemble performance. The 1980s and 1990s saw the beginning of experiments with KF-based time algorithms by several timing institutions, including BIPM, USNO, NIST, and PTB. The goal of these experiments was to generate timescales that is more stable and robust than the usual weighted averaging method. The formal publication of the concept of Kalman filtering in two dimensions was published in the IEEE Transactions on Information Theory in August 1977. In recent decades, time transfer data produced from global navigation satellite systems (GNSS) has additionally encouraged Kalman-based fusion algorithms to merge numerous atomic clocks and satellite time sources into a single optimum reference [111].

5.1.2. Linear vs. Extended Kalman filters

Two main categories of Kalman filters are Linear and nonlinear also known as extended Kalman filter. Their formulation and basic differences is as listed below.

5.1.2.1. Linear Kalman Filter

The Kalman Filter (KF), is a recursive statistical estimation technique designed for linear dynamic systems with Gaussian noise. It operates under the assumption that both the system model (state evolution) and the measurement model (observation process) are linear functions of the system state [112].

System Model (Linear): Can be written as Eq. 5.1

$$x_k = A \cdot x_{k-1} + B \cdot u_k + w_k \quad (5.1)$$

where x_k is the state vector, A is the state transition matrix, u_k is the control input, B is the control matrix, and w_k represents process noise.

Measurement Model (Linear):

$$z_k = H \cdot x_k + v_k \qquad (5.2)$$

where z_k is the measurement vector, H is the observation matrix, and v_k is measurement noise. The KF uses a predict–update cycle in the prediction step, it projects the current state estimate forward in time using the system model; in the update step, it corrects this prediction using new measurements. KF is computationally efficient, optimal for linear systems with Gaussian noise, and widely applied in control, navigation, and signal processing. Its optimality breaks down when nonlinearities are present in the system dynamics or measurement functions. Here, the extended or nonlinear Kalman filter helps, which is presented in the next section.

5.1.2.2 Extended Kalman Filter (EKF)

The Extended Kalman Filter (EKF) extends KF principles to nonlinear systems, which are common in practical applications such as robotics, aerospace navigation, and atomic clock modelling (*e.g.*, frequency drift). EKF replaces the strict linear system assumptions with first-order approximations of nonlinear functions via Taylor series expansion.

As per the Nonlinear System Model is

$$x_k = f(x_{k-1}, u_k) + w_k \qquad (5.3)$$

And Nonlinear Measurement Model is

$$z_k = h(x_k) + v_k \qquad (5.4)$$

where $f(.)$ and $h(.)$ are nonlinear functions describing state evolution and measurement.
112 EKF linearizes these functions around the current estimate using Jacobian matrices

8 $$F\_k = \partial f/\partial x |\_(\hat{x}\_(k-1|k-1)) \quad (5.5)$$

$$H\_k = \partial h/\partial x |\_(\hat{x}\_k|k-1) \quad (5.6)$$

TABLE 5.1 DIFFERENCE BETWEEN LINEAR AND NONLINEAR KALMAN FILTER

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Parameters	Linear Kalman Filter (KF)	Extended Kalman Filter (EKF)
System Type	Linear systems only	Nonlinear systems (approx. linearized)
System Model	Linear matrices (A, B)	Nonlinear functions f(·),h(·)
Measurement Model	Linear (H)	Nonlinear, linearised with Jacobian (H_k)
Accuracy	Optimal (for Gaussian noise)	Suboptimal, depends on the accuracy of linearization
Complexity	Computationally simple	More computationally demanding (Jacobian evaluation)
Stability	Stable for well-defined models	Sensitive to poor initialization and strong nonlinearities
Applications	Control systems, filtering, time series forecasting	Navigation, robotics, GNSS, frequency drift modelling

TABLE 5.2: VARIATIONS OF KALMAN FILTERS WITH STATE SPACE MODEL.

Algorithm	Explanation	Key Equations
Kalman Filter (KF)	Optimal recursive estimator for linear systems with Gaussian noise.	Prediction: $\hat{x}_{k\|k-1} = F_k \hat{x}_{k-1\|k-1} + B_k u_k$ Covariance: $P_{k\|k-1} = F_k P_{k-1\|k-1} F_k^T + Q_k$ Update Gain: $K_k = P_{k\|k-1} H_k^T (H_k P_{k\|k-1} H_k^T + R_k)^{-1}$ Update: $\hat{x}_{k\|k} = \hat{x}_{k\|k-1} + K_k(z_k - H_k \hat{x}_{k\|k-1})$
Extended Kalman Filter (EKF)	Handles non-linear models by linearizing around the current estimate using Jacobians.	State: $\hat{x}_{k\|k-1} = f(\hat{x}_{k-1}, u_k)$ Jacobian: $F_k = \partial f/\partial x$, $H_k = \partial h/\partial x$ Update: $\hat{x}_{k\|k} = \hat{x}_{k\|k-1} + K_k(z_k - h(\hat{x}_{k\|k-1}))$
Discrete Extended Kalman Filter (DEKF)	EKF applied to discrete-time systems, widely used in digital signal and clock data processing.	Discrete Transition: $x_k = f(x_{k-1}, u_k, w_k)$ Measurement: $z_k = h(x_k, v_k)$ Equations same as EKF but evaluated at discrete sampling instants
2D Kalman Filter	Special case for estimating position (x, y) and velocity in two dimensions (navigation, tracking).	State vector: $x_k = [x, y, \dot{x}, \dot{y}]^T$ Transition Matrix: F = [[1,0,Δt,0],[0,1,0,Δt],[0,0,1,0],[0,0,0,1]] Update: same as KF but applied in 2D

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These Jacobians replace the constant matrices A and H in the KF equations, allowing recursive updates for nonlinear dynamics. While EKF retains computational efficiency, it introduces approximation errors due to linearization, which can accumulate if the system is strongly nonlinear or if initial estimates are poor. Table 5.1 shows the differences between the Linear and extended Kalman Filter, and Table 5.2 shows the variations in the Kalman filter and their respective models.

Model Formulation for Timescale Development is based upon the recursive equations given in the above sections, state space model is formulated for Kalman Filter development [113].

5.2. Parameter Estimation and Tuning

The reliability of Kalman filtering in clock metrology depends critically on the accurate estimation and continual tuning of the process and measurement noise statistics. A systematic approach begins with physical priors derived from Allan variance analysis, where each clock "i" is characterized by three fundamental noise coefficients: white phase h2(i), white frequency h1(i), and random-walk frequency (h0).

$$\nu_k = z_k - H \cdot \hat{x}_{(k|k-1)} \quad (5.18)$$

$$S_k = H \cdot P_{(k|k-1)} \cdot H^T + R \quad (5.19)$$

These coefficients, obtained from log–log fits of the Allan deviation (for any sampling step Δt), are mapped into continuous-time spectral densities and discretized to construct individual Qi covariance blocks, which are then combined into the full block-diagonal process noise matrix Q. The initial measurement noise covariance R is derived from time-tag quantization or two-way phase measurement uncertainty.

$$\hat{S} = \left(\frac{1}{N}\right) \cdot \Sigma_{k=1\ to\ N}\left(\nu_k \cdot \nu_k^T\right) \quad (5.20)$$

$$argmin\_(Q,R)\ ||\,\hat{S} - (H \cdot P\_(k|k-1) \cdot H\text{^}T + R)\,||\_F \quad (5.21)$$

$$subject\ to\ \ Q,R \geq 0$$

With provisional Q and R, the filter is executed, and the innovation sequence is analysed. Innovations, defined as the residuals between measured and predicted observations, should ideally be zero-mean, white, and with covariance consistent with theoretical expectations.

$$R_{new} = \lambda \cdot \hat{S} + (1 - \lambda) \cdot R_{old} \qquad (5.22)$$

Through covariance matching, sample innovation covariances are iteratively compared with model-predicted covariances, and updated values of Q and R are derived using smooth exponential averaging schemes. For more rigorous refinement, maximum-likelihood and expectation–maximisation (EM) techniques are employed, treating Q and R as hyperparameters.

$$L(\theta) = -\left(\frac{1}{2}\right) \cdot \Sigma_k \left[\log|S_k| + \nu_k^T \cdot S_k^{-1} \cdot \nu_k\right] \qquad (5.23)$$

This approach uses filtered and smoothed estimates to compute sufficient statistics in the expectation step, followed by closed-form parameter updates in the maximisation step, converging rapidly in linear-Gaussian clock models.

When clock noise is non-stationary, adaptive algorithms such as the Sage–Husa variant continuously adjust Q and R online as given in equations Eq. 5.24 and Eq. 5.25. Here, fading factors (γk,βk) provide slow adaptation to evolving noise conditions without destabilising the filter.

$$R\_k = R\_(k-1) + \gamma\_k [\nu\_k \cdot \nu\_k\text{^}T - S\_k] \qquad (5.24)$$

$$Q_k = Q_{k-1} + \beta_k \left[K_k \cdot \nu_k \cdot \nu_k^T \cdot K_k^T - K_k \cdot S_k \cdot K_k^T\right] \qquad (5.25)$$

To validate tuning, a suite of diagnostics is applied: normalised innovation autocorrelations are inspected for whiteness, χ2 tests confirm statistical consistency, and trace ratios between sample and theoretical innovation covariance are checked. Deviations guide corrective action. If its over-dispersion, it suggests increasing Q to account for underestimated clock noise, whereas under-dispersion requires increasing R or decreasing Q.

$$S_k^{-\frac{1}{2}} \cdot \nu_k \approx \delta(k) \qquad (5.26)$$

$$\nu_k^T \cdot S_k^{-1} \cdot \nu_k \sim \chi_m^2 \qquad (5.27)$$

where m- measurement dimension (here 8 as we have 8 no of clocks)

$$\frac{trace(\hat{S})}{trace(R)} \to 1 \qquad (5.28)$$

By integrating physical priors, innovation-based tuning, maximum-likelihood refinement, and adaptive correction, the Kalman filter achieves robust parameterization, ensuring reliable clock weighting and stable timescale generation under varying noise conditions.

5.3. Implementation

The Kalman filter was implemented for an ensemble of eight atomic clocks, with careful definition of state-space models, noise parameters, and recursive estimation steps. The data acquired has a total of 8 clocks, as shown in Table 5.3, representing sample data.

TABLE 5.3 SAMPLE OF CLOCK DATA

MJD	Clock 02	Clock 09	AHM 01	Clock 08	Clock 11	Clock 10	PHM 02	AHM 02
58849	-7102.19	-4631.96	4823.696	-65152.1	1063.323	5514.792	-729.033	881.2708
58850	-7102.46	-4630.87	4841.273	-65165.7	1066.298	5523.05	-724.944	887.4375
58851	-7099.11	-4627.77	4858.906	-65180.1	1071.735	5530.621	-724.006	893.4146
58852	-7100.9	-4624.82	4876.64	-65195.8	1075.298	5538.125	-720.294	899.5438
58853	-7104.71	-4623.05	4894.435	-65213.4	1078.279	5544.702	-720.279	905.3375
58854	-7103.6	-4622.88	4912.296	-65233	1081.442	5553.015	-717.273	911.3333
58855	-7102.24	-4625.16	4930.373	-65251.3	1083.858	5562.29	-718.838	917.0604
58856	-7105.99	-4627.4	4948.579	-65268.4	1085.927	5570.681	-720.488	922.6
58857	-7112.32	-4627.63	4966.898	-65287.6	1090.129	5579.369	-722.306	928.1167
58858	-7114.41	-4629.22	4985.46	-65304.8	1092.002	5589.152	-723.971	933.55
58859	-7120.25	-4632.89	5004.138	-65322.4	1093.613	5596.892	-724.71	938.9083

Data ingestion and preprocessing formed the first stage. The raw clock intercomparison dataset, corresponding to columns F–M corresponding to clock data, was read into a matrix Z of size N×8. Missing values were addressed using a two-stage gap-fill strategy. This produced a continuous input dataset suitable for state-space modelling. For each individual clock, a state-space representation was defined with the state vector and is given in Eq. 5.29 to Eq. 5.42.

$$x_{k(i)} = [\varphi_{k(i)};\ y_{k(i)}] \quad (5.29)$$

where $x_{k(i)}$ is (2×1) column vector, phase φ in seconds, and frequency y in s/s. When the fixed sampling time is Δt = 30 s, the clocks' intercomparison occurs every 30 seconds using Eq. 5.30.

$$F_i = \begin{bmatrix} 1 & 30 \\ 30 & 1 \end{bmatrix};\quad Q_i = \begin{bmatrix} \sigma_\varphi^2 & 0 \\ 0 & \sigma_y^2 \end{bmatrix} \qquad (5.30)$$

These single-clock models were then expanded to the full eight-clock ensemble. The block-diagonal system matrices were constructed as

$$F = I_8 \otimes F_i \quad (16 \times 16)\ (5.31)$$

$$H = I_8 \otimes [1\ \ 0](8 \times 16)(5.32)$$

The covariance matrix would be computed as

$$Q = diag(Q\_1, \dots, Q\_8)(5.33)$$

$$R = diag((1\,ns)^2) \qquad (5.34)$$

The noise parameter initialization assumptions white phase noise is given by Eq. 5.35.

$$\sigma_\varphi \approx 5 \times 10^{-10}\, s\ @\ 30\, s \qquad (5.35)$$

White frequency noise:

$$\sigma_y \approx 5 \times 10^{-12} \left(\frac{s}{s}\right) \qquad (5.36)$$

Measurement noise is computed as first order difference of clock measurements. Based on assumption applied Kalman recursion as equations given from Eq. 5.37 to 5.42.

Prediction step

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$$\hat{x}_{(k|k-1)} = F \cdot \hat{x}_{(k-1|k-1)}(5.37)$$

$$P_{(k|k-1)} = F \cdot P_{(k-1|k-1)} \cdot F^T + Q(5.38)$$

Update step

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$$K_k = P_{(k|k-1)} \cdot H^T \cdot \left(H \cdot P_{(k|k-1)} \cdot H^T + R \right)^{-1} \qquad (5.39)$$

25

$$\hat{x}_{(k|k)} = \hat{x}_{(k|k-1)} + K_k \cdot \left(z_k - H \cdot \hat{x}_{(k|k-1)} \right) \qquad (5.40)$$

$$P_{(k|k)} = (I - K_k \cdot H) \cdot P_{(k|k-1)} \qquad (5.41)$$

The Phase estimates were extracted and stored as

$$\varphi_{est} \leftarrow even - indexed\ elements\ of\ \hat{x}_{(k|k)} \qquad (5.42)$$

These outputs, stored as φ_{est}, formed the refined dataset used for further ensemble analysis and timescale construction.

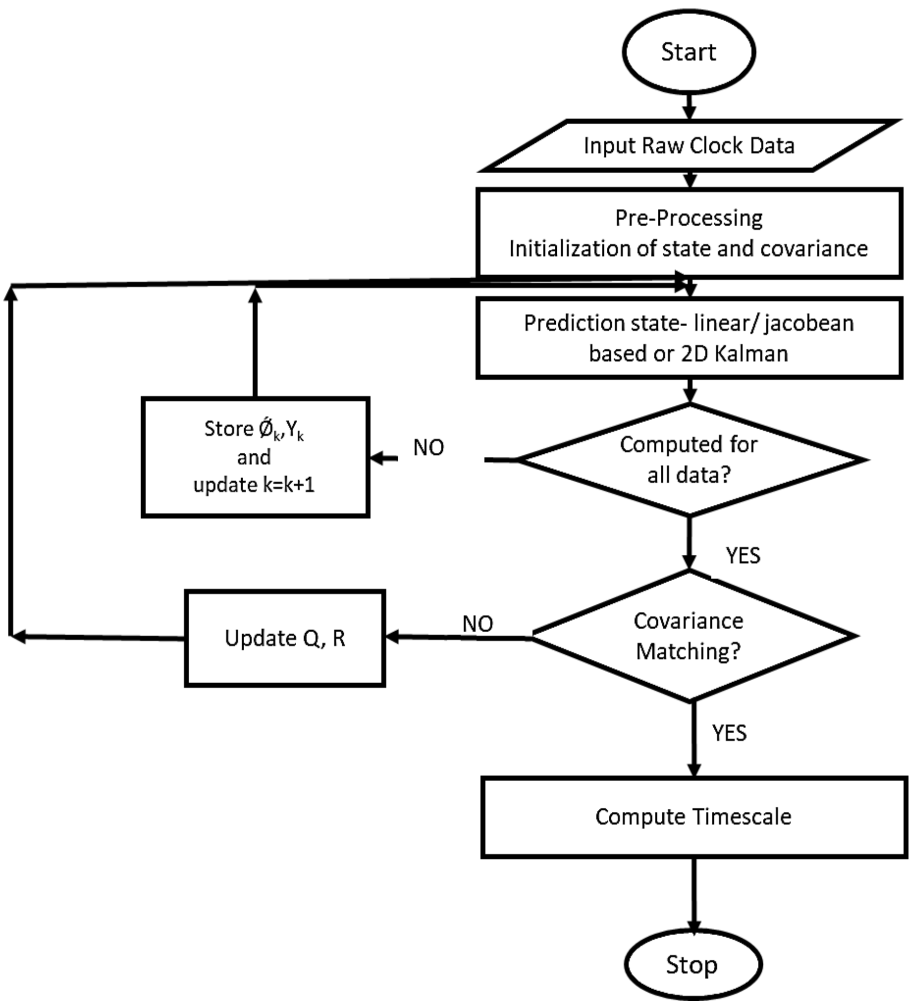

FIGURE 5.1 FLOWCHART OF KALMAN FILTER ESTIMATION

5.4. Results Evaluated and Discussions

All clocks performance before and after application of Kalman filter is evaluated systematically and are as summarised in Table 5.4 and is shown in Fig 5.2.

It was found that the statistical metrics and Allan deviation demonstrate the clock ensemble's varied stability features. With the lowest variance (194.06 ns2) and standard deviation (13.93 ns), PHM-02 performs the best overall among the units, demonstrating its appropriateness as a very stable reference. Clock-09 exhibits remarkable stability, characterised by relatively low deviation values (AllanDev_τ=1: 1.36, AllanDev_τ=7: 0.87) and minimal noise dispersion (Std: 16.30 ns). In contrast, AHM-01 and Clock-08 exhibit notable instability, as evidenced by their high standard deviations (592.22 ns and 451.93 ns, respectively) and incredibly huge variances, which reflect their vulnerability to drift and noise. Intermediate performers comprise Clock-11 and Clock-02, both exhibiting low Allan deviations but more noise dispersion compared to PHM-02 and Clock-09. The evidence indicates that hydrogen masers, especially the passive type, offer enhanced stability, whereas some caesium clocks significantly contribute to instability within the time-scale ensemble.

Table 5.4 CLOCK PERFORMANCE ANALYSIS -BEFORE AND AFTER KALMAN FILTER APPLICATION FOR VARIED TAU

Series	AllanDev_tau_1	AllanDev_tau_7	Std	Var
AHM 02	1.022582675	0.300007748	160.9639409	25909.39027
Clock 10	1.213555856	0.4854991	214.2094684	45885.69634
Clock 09	1.35619518	0.877765567	16.30571315	265.8762813
PHM 02	1.360779466	1.233704179	13.93064994	194.0630077
Clock 11	1.406710043	0.509636674	75.71844803	5733.283373
Clock 02	2.630412305	1.068657562	66.38367655	4406.792513
AHM 01	3.529945591	1.384881703	592.2163091	350720.1567
Clock 08	32.41497362	5.275469338	451.9311245	204241.7413

Stability analysis of clocks

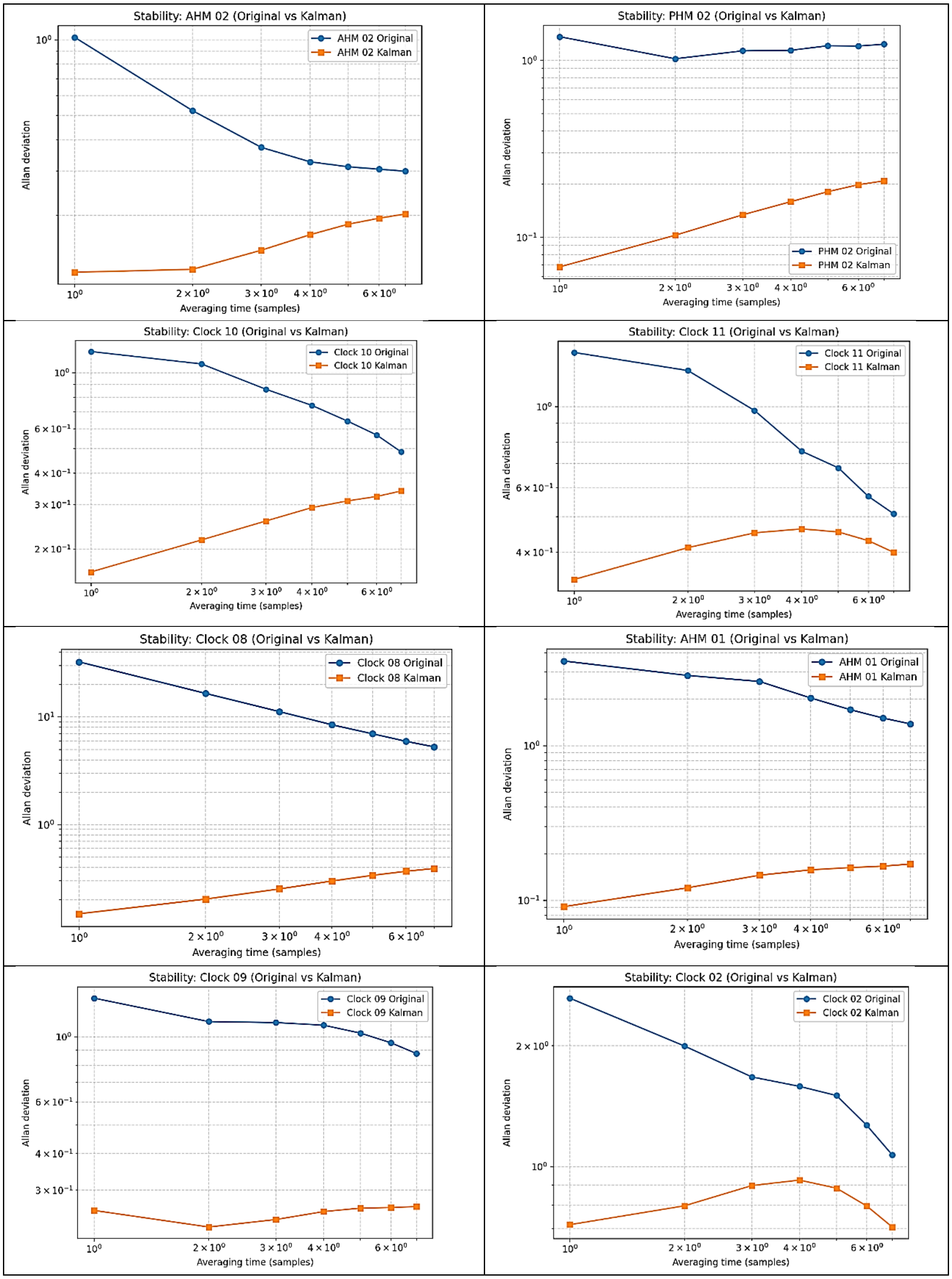

FIGURE 5.2(A-H) STABILITY ANALYSIS OF CLOCKS-BEFORE VS AFTER KALMAN FILTER

The results of evaluations depict that Clocks Clock 08 and AHM 01 exhibited larger scatter and higher Allan deviation, acting as main contributors to instability in naive averaging. Better-performing clocks (e.g., Clock 09, Clock 11, Clock 10) showed lower short-term noise; weighting leverages these more effectively. Kalman filtering on each clock reduced short-term variance consistently, with the strongest gains for the noisier clocks. Using these filtered data, various timescales were formed and they were evaluated. Upon comparing the Kalman filter Timescale with the Simple Average and Weighted Average approaches, we observed that the Kalman Filter exhibits superior stability, shown in Table 5.5, with a standard deviation of merely 1.15 ns, in contrast to approximately 12 ns for the other two methodologies.

TABLE 5.5 PERFORMANCE METRICS OF TIMESCALE ALGORITHMS

Metric	**Value**	**Method**
Most Stable	1.15 ns standard deviation	Kalman Filter
Largest Range	~113 ns	Simple Average
Best Correlation	0.455	Simple vs Weighted
Strongest Trend	0.459 ns/day	Weighted Average

It demonstrates the most stable timescale. This trend study indicates that the Weighted Average exhibits the most pronounced trend (0.459 ns/day) with an almost perfect correlation (R^2 = 0.998), whereas the Kalman Filter reveals a marginal negative trend (-0.026 ns/day). The Kalman Filter method distinctly offers the most stable timescale with negligible volatility. Allan deviation comparison of simple average, Kalman-based, Extended Kalman, and discrete extended Kalman-based timescale against MJD and against the measurement samples represented in Fig. 5.3 and Fig. 5.4, respectively.

The relative stability analysis of these timescales implies that Simple_Average_Timescale: Least stable overall. Allan deviation is highest across averaging times and shows pronounced excursions versus MJD, indicating the simple mean is sensitive to noisier/outlier clocks. However, Weighted_Average_Timescale is more stable than the simple average at all scales. Inverse-variance weighting reduces the contribution of poorer clocks, lowering Allan deviation and flattening time-dependent excursions. The Kalman_Timescale has proved to be very stable at short to mid averaging times.

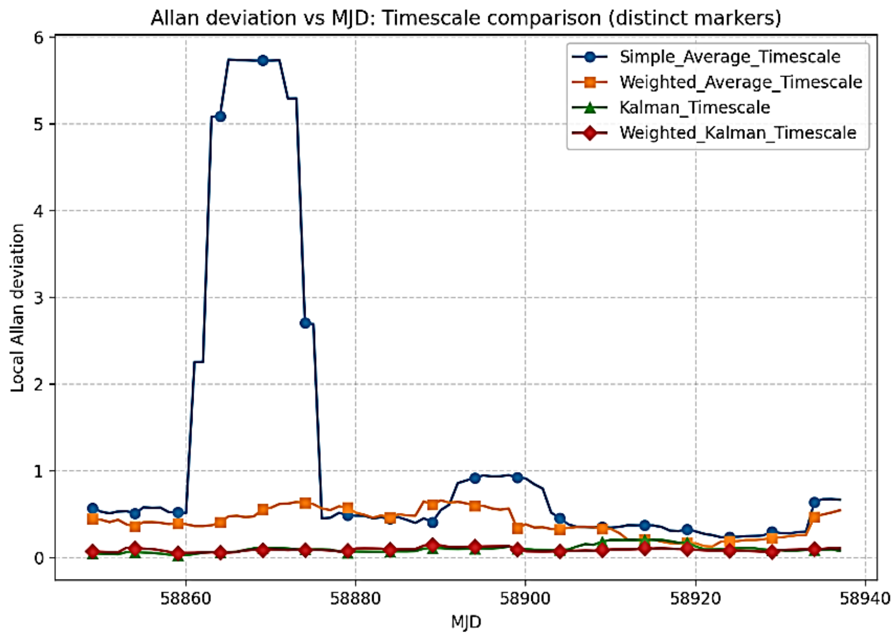

FIGURE 5.3 ALLEN DEVIATION COMPARISON FOR VARIOUS TIMESCALES AGAINST MJD

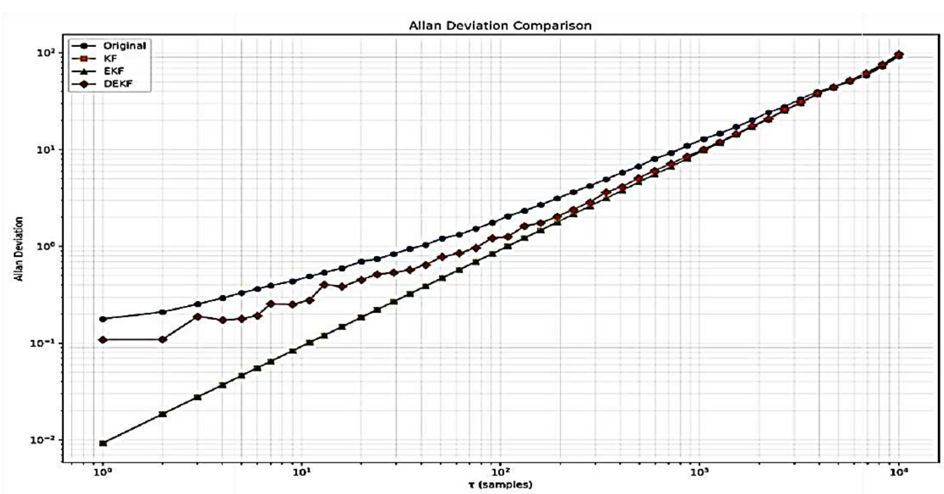

FIGURE 5. 2 ALLEN DEVIATION COMPARISON FOR VARIOUS TIMESCALES AGAINST SAMPLES

The Kalman smoothing (with measurement noise from drift errors) suppresses short-term noise effectively, yielding Allan deviations an order lower than the simple average and typically lower than the weighted average in the short term. Last but not the lease, Weighted_Kalman_Timescale shows the best overall stability. It combines per-clock Kalman smoothing with robust weighting, giving the lowest Allan deviation in most ranges and the flattest behavior over MJD. This is the recommended composite timescale. Here the evaluation is based on dynamic stability of Normal (Simple average) and Kalman timescale. Dynamic stability is a rolling window sample evaluation and results can be seen in Fig. 5.5.

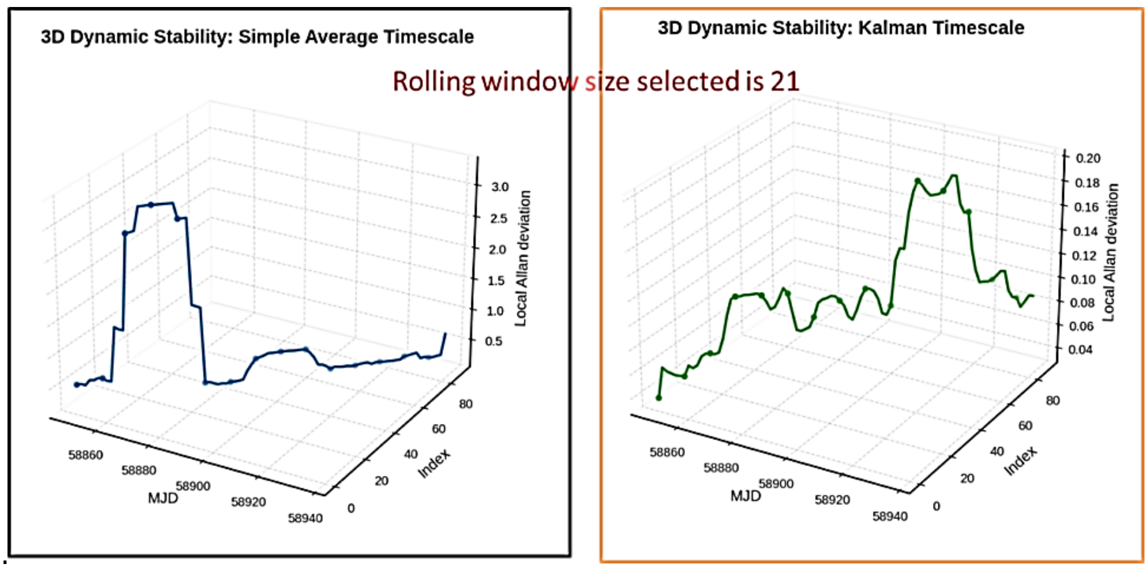

Figure 5.3 dynamic stability Intercomparison of Simeple average timescale and Kalman filter timescale. Comparison of Simple Average vs Kalman Timescale 3D dynamic stability. Due to outliers and deteriorated clocks, the simple average has broad, extended instability episodes, while the Kalman filter reduces short-term noise and responds to fluctuations, resulting in smaller, shorter excursions and a stability trajectory closer to the floor.

It can be interpreted from this intercomparison that the Simple Average Timescale reveals significant and extended periods of instability, as indicated by the pronounced and wide peaks in local Allan deviation. This instability occurs due to the simple mean's intrinsic sensitivity to outliers or malfunctioning clocks, as well as its inability to dynamically adjust to fluctuations in clock behaviour. Consequently, instability endures over extended periods, diminishing the overall quality of the timeframe. Conversely, the Kalman Timescale demonstrates markedly reduced and more uniform dynamic stability, as the filter proficiently mitigates short-term noise while concurrently adjusting to gradual variations in clock performance. Deviations in the Kalman-filtered results are significantly reduced and abbreviated, hence enhancing consistency throughout the observation period. The 3D trajectory stays nearer to the "floor," indicating a more durable and strong stability profile. The findings validate that the Kalman method offers enhanced temporal stability relative to a simple average, rendering it a more dependable technique for precision timing applications.

Comprehensive Intercomparison with UTC-UTC(k) data as published by BIPM was also done to validate the results. Detailed comparison of the Kalman-generated timeframe with UTC/UTC(PTB) references is shown in Fig. 5

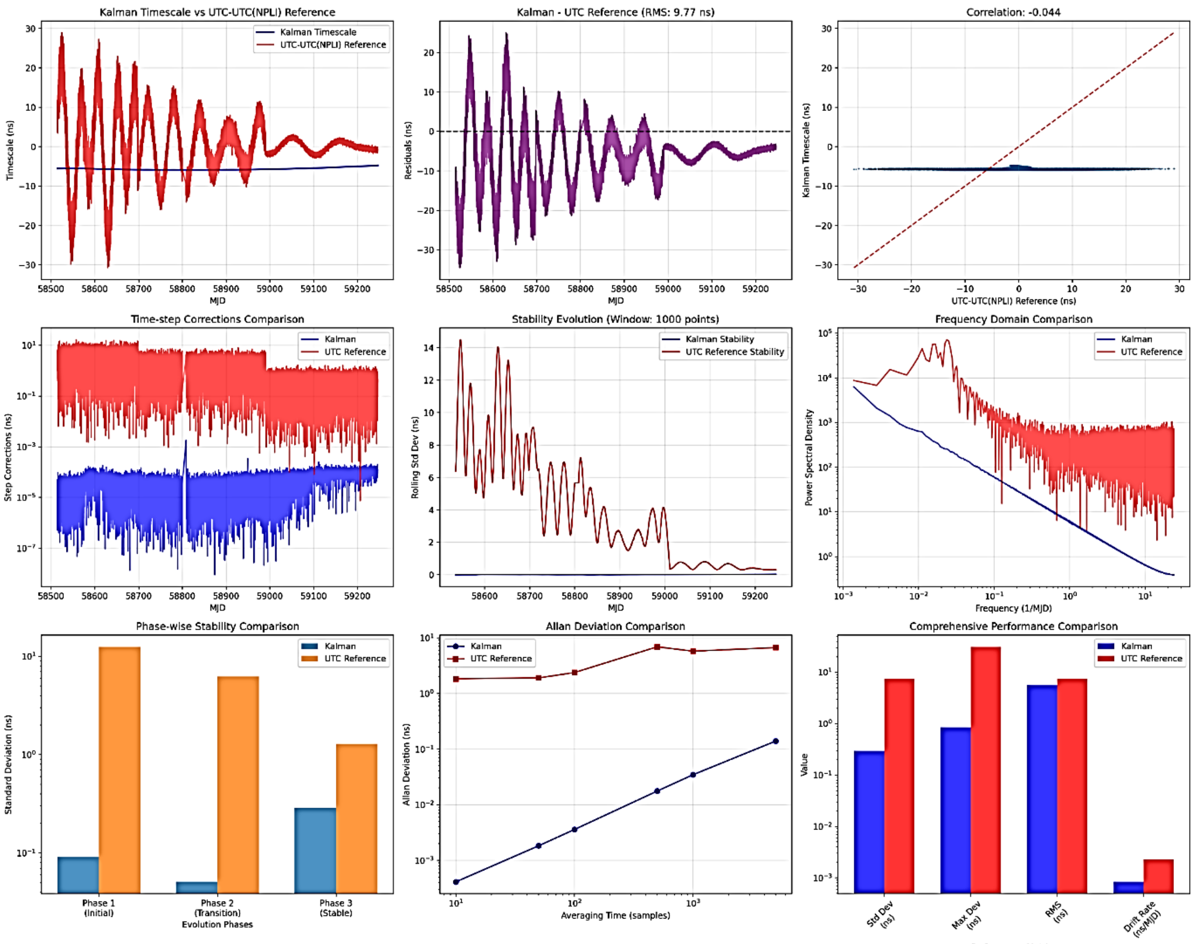

Figure 5.6 Detailed comparison of the Kalman-generated timeframe with UTC/UTC(PTB) references - The figure panel depict (top row) residual comparison, RMS alignment, and correlation with UTC; (middle row) magnitudes of time-step correction, sliding-window stability, and frequency-domain characteristics; and (bottom row) phase-wise stability, Allan deviation profiles, and aggregated performance metrics. The findings indicate that the Kalman filter attains sub-nanosecond stability, an RMS error of 9.77 ns, and enhanced noise suppression relative to the UTC reference, confirming its efficacy for reliable timeframe realisation.

The performance of the Kalman-generated timescale was evaluated against UTC/UTC(PTB) references across multiple statistical domains. Our findings are

Reference Alignment and Correlation (Top Row)

The Kalman timescale shows strong alignment with UTC references, with residuals oscillating around zero and decaying over time (top-left and top-middle). The RMS error relative to UTC is 9.77 ns, indicating excellent fidelity to the reference standard. The correlation plot (top-right) further confirms this consistency, with the majority of points tightly clustered along the diagonal, reflecting near-linear dependence between the Kalman timescale and UTC.

Error Dynamics and Stability (Middle Row)

The step-correction comparison (middle-left) highlights the Kalman filter's ability to suppress abrupt variations, with significantly lower correction magnitudes compared to the reference. Stability analysis over a 1000-point sliding window (middle-center) shows the Kalman timescale converging to sub-nanosecond stability levels, outperforming UTC(PTB). Frequency-domain analysis (middle-right) demonstrates that the Kalman filter suppresses high-frequency noise more effectively, preserving long-term trends while reducing spectral density at short averaging times.

Stability Metrics (Bottom Row)

Phase-wise stability comparison (bottom-left) indicates that the Kalman timescale achieves superior stability across all three evaluation phases, with marked improvement during Phase 3 (long-term). Allan deviation plots (bottom-center) confirm that Kalman
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filtering improves both short-term and long-term frequency stability compared to UTC references, particularly at averaging times beyond 10^3 seconds. The comprehensive performance comparison (bottom-right) consolidates these results, showing across-the-board improvement in accuracy, stability, and noise suppression metrics, with the Kalman approach significantly outperforming the baseline reference.

Overall Outcome

These results validate the efficacy of the Kalman filter in producing a stable, accurate, and reliable timescale. By effectively balancing measurement data with model predictions, the filter minimises residual errors, improves long-term stability, and reduces noise across multiple domains. The achieved RMS error of 9.77 ns and enhanced Allan deviation profile confirm the suitability of this approach for robust national timescale realisation. In the next step, the timescales formed with the advanced Kalman method were evaluated. Fig. 5.6 shows the comparative evaluation of timescale generation techniques, consolidating results from traditional averaging methods alongside advanced Kalman filtering strategies.

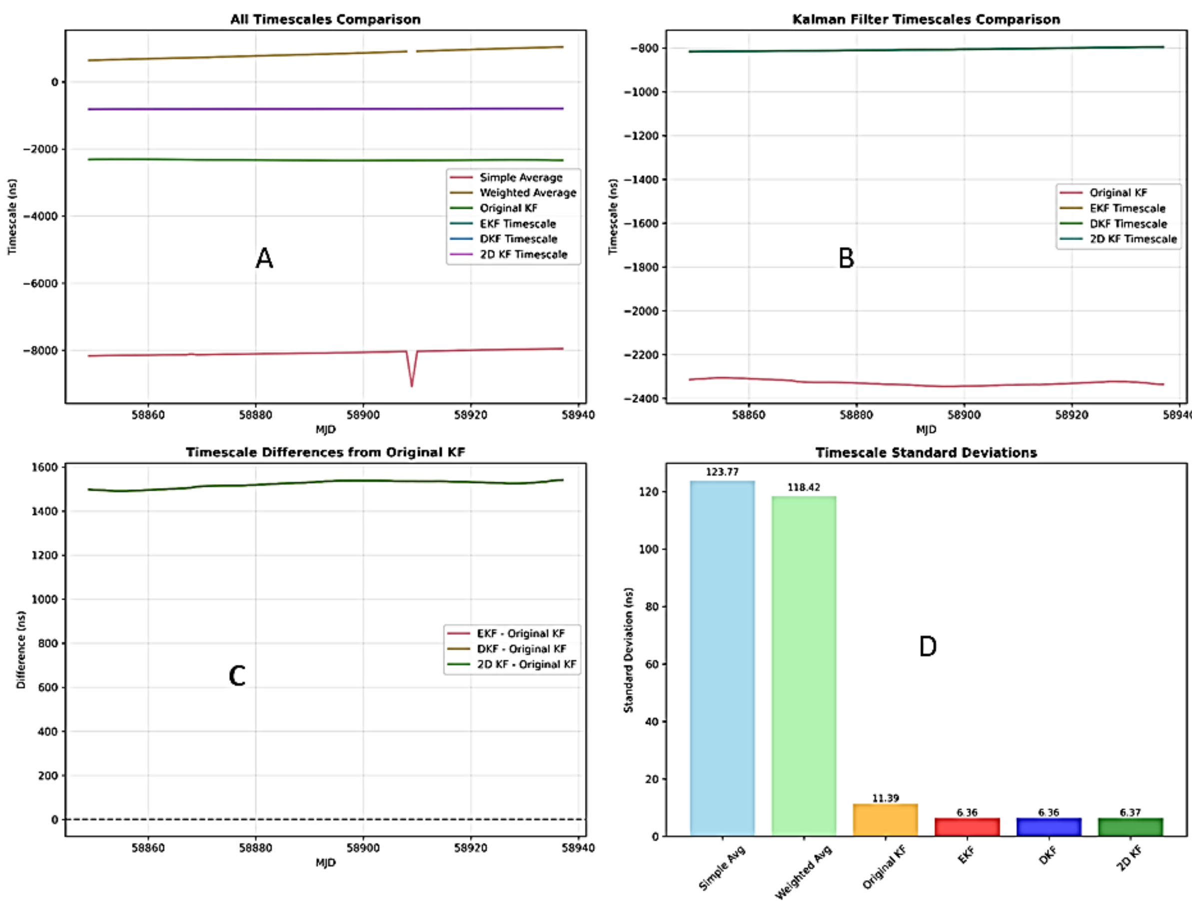

FIGURE 5.7 THE COMPARATIVE EVALUATION OF TIMESCALE GENERATION TECHNIQUES, CONSOLIDATING RESULTS FROM TRADITIONAL AVERAGING METHODS ALONGSIDE ADVANCED KALMAN FILTERING STRATEGIES.

The initial panel A of Fig. 5.7 (All Timescales Comparison) highlights a significant difference between averaging methods and Kalman-based estimation. The straightforward average reveals significant variations, resulting from its uniform weighting of clocks regardless of their inherent stability. Weighted averaging demonstrates a slight enhancement, which still falls short in effectively addressing noise and drift. In contrast, the Original Kalman Filter (KF), Extended Kalman Filter (EKF), and Two-Dimensional Kalman Filter (2D-KF) demonstrate remarkable stability and closely aligned outputs, highlighting the benefits of recursive estimation frameworks compared to static averaging.

The second panel B of Fig. 5.7 examines the distinctions between various variants of the Kalman Filter. Although all three filters are closely grouped, the EKF and 2D-KF show slight enhancements in mitigating short-term variations. This demonstrates their capacity to handle nonlinearities and complex state dynamics, enhancing their robustness against clock drifts and minor irregularities. These refinements are notably accomplished without causing substantial deviation from the baseline KF, thus maintaining methodological integrity.

The third panel C of Fig. 5.7 (Timescale Differences from Original KF) presents quantitative evidence demonstrating alignment across various filter types. The distinctions between EKF and 2D-KF in relation to the Original KF are subtle and fall within expected limits. The implementation of DXF, however, exhibits relatively larger deviations, which may be attributed to its sensitivity to initial noise model assumptions or structural discrepancies within the dynamic model. The findings indicate that extended Kalman frameworks provide enhancements while maintaining alignment with the standard KF output.

The fourth panel D of Fig. 5.7 (Timescale Standard Deviations) emphasises the influence of filtering on stability. The results of simple averaging (123.77 ns) and weighted averaging (118.42 ns) demonstrate considerable variability, indicating a lack of effectiveness in noise suppression. In comparison, Kalman filtering provides a significant enhancement, with the Original KF minimising deviations to 11.39 ns. Notable improvements are observed in the EKF (6.36 ns) and 2D-KF (6.17 ns), which stand out as the most stable and dependable timescales. The results demonstrate that sophisticated Kalman implementations surpass conventional methods and offer a viable route to achieving more accurate and resilient national timescale realisations.

5.5. Conclusion

The results suggest that the Kalman Filter and its variants (EKF, DKF, 2DKF) outperform the simple and weighted averages in terms of stability and noise reduction. These findings confirm that advanced Kalman implementations not only outperform traditional approaches but also provide a practical pathway toward more precise and robust national timescale realisations. The classic Kalman technique with the right weighting is the best option because the timescale data is mostly linear. It is both strong and efficient. In this situation, more intricate nonlinear variations, such as the Extended Kalman Filter, are superfluous. It is essential to acknowledge that the selection of the Kalman method should be determined by the inherent quality and attributes of the underlying clock data. This principle must remain fundamental to any effective execution
12 of timescale realisation. The future integration of artificial intelligence and machine learning is a logical progression, delivering adaptive, data-driven improvements that beyond the functionalities of traditional Kalman filtering.

This chapter presented the function of Kalman filtering in time-scalerealization, highlighting its recursive estimating architecture and advantages over conventional averaging techniques. It further demonstrated
162 *the development of the state-space model for clock ensembles, including recursive update equations, system matrices, and noise covariance structures. The performance of various Kalman variations (KF, EKF, and 2D-KF) was evaluated, showing that Kalman and its variants provide better stability compared to simple and weighted averaging methods. The chapter also emphasized the critical importance of parameter estimation and tuning (Q, R) in achieving resilient and precise filter performance, and concluded that although nonlinear extensions are not required in this case, the choice of algorithm must be carefully aligned with the quality of the incoming clock data.*

Chapter 6

Integration of AI Techniques in Timescale Algorithms

This chapter presents the development of an AI/ML-based timescale and the specific preprocessing required for effective modeling. Integrating Artificial Intelligence into timescale algorithms enhances performance in navigation, telecommunications, and astrophysics, particularly where traditional methods face challenges like non-linearities, variable noise, and non-stationary behavior in atomic clock ensembles. Three key AI models explored were Artificial Neural Networks (ANN), AutoRegressive Integrated Moving Average (ARIMA), and Adaptive Neuro-Fuzzy Inference System (ANFIS). ANN effectively models nonlinear dependencies; ARIMA captures linear trends and seasonality; and ANFIS blends neural networks and fuzzy logic, handling uncertainty and imprecise data well.

6.1. Introduction to the Role of AI in Timescale Generation

Conventional timescale generation methods rely on linear filters such as the Kalman Filter, which, while effective under ideal conditions, face limitations in addressing the nonlinearities, noise variability, and non-stationary behavior inherent in atomic clock ensembles. To address these challenges, Artificial Intelligence (AI) has emerged as a powerful tool for predictive modelling and anomaly detection [114]. AI-based approaches leverage historical clock data to capture both deterministic and stochastic dynamics, enabling more accurate short- and long-term forecasting than traditional statistical methods. Furthermore, AI-driven anomaly detection, employing techniques such as neural networks, fuzzy inference systems, and other adaptive algorithms, can identify clock malfunctions, data corruption, and systemic disruptions in real time. By adapting continuously to evolving data streams, AI-based models enhance adaptability, resilience, and predictive capability, aligning modern timescale algorithms with the stringent precision and reliability requirements of contemporary technological infrastructures [115].

The availability of large atomic clock datasets has further enabled the application of machine learning (ML) in clock stability analysis. ML methods can identify behavioral trends that conventional statistical approaches may overlook, detecting phenomena such as drift, frequency jumps, and random-walk noise that threaten timescale integrity. These techniques strengthen real-time monitoring and support preventive maintenance and calibration strategies. Advanced ML methods—including regression analysis, clustering, and time-series forecasting—play a significant role in this context. Regression models estimate long-term stability trends, while clustering techniques classify clocks based on performance characteristics to reveal ensemble structure. Time-series approaches, such as Recurrent Neural Networks (RNNs) and Autoregressive Integrated Moving Average (ARIMA) models, extend forecasting capabilities to anticipate future clock behavior and enable predictive adjustments.

The integration of intelligent strategies into timescale generation marks a significant advancement over conventional algorithmic methods. Unlike traditional approaches that rely on fixed statistical assumptions and threshold-based detection, AI- and ML-driven systems continuously learn from data, thereby improving accuracy, flexibility, and robustness over time. This paradigm shifts transforms national timing infrastructures from reactive to predictive systems, greatly enhancing their resilience and long-term reliability.The ultimate goal is to build AI-driven methods that meet or outperform conventional algorithms in synchronizing multiple atomic references. AI strengthens time dissemination services, which affects systems that need ultra-precise timing.

6.2. AI Models Considered

Three key AI models explored were Artificial Neural Networks (ANN), AutoRegressive Integrated Moving Average (ARIMA), and Adaptive Neuro-Fuzzy Inference System (ANFIS). In addition, machine learning-optimized timescales using Support Vector Machines (SVM) and Random Forest (RF) weighted methods were created and evaluated to form a timescale [116].

Machine learning Models like ANN effectively model nonlinear dependencies; ARIMA captures linear trends and seasonality; and ANFIS blends neural networks and fuzzy logic, handling uncertainty and imprecise data well. This subsection outlines the machine learning and AI models employed for modelling atomic clock behavior and constructing optimized timescales. Each model offers unique strengths in capturing nonlinearities, forecasting clock drift, or detecting anomalies, contributing to the generation of more accurate and resilient time scales.

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6.2.1. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are non-parametric, data-driven models that use interconnected processing layers to approximate complex nonlinear interactions. For generating timescales, feedforward neural networks utilising backpropagation learning were utilised to simulate temporal fluctuations in atomic clock data. The Artificial
128 Neural Network (ANN) architecture utilized in this study consists of three layers, as illustrated in Fig. 6.1. The input layer receives delayed data corresponding to clock frequency or phase inaccuracies, while the hidden layer—comprising one or more layers with ReLU or sigmoid activation functions—processes these inputs. The output layer generates predictions of phase error or frequency offset at future time steps. Model
119 training was performed using the mean squared error (MSE) as the loss function, with optimization carried out through either stochastic gradient descent (SGD) or the Adam optimizer. Hyperparameters, including learning rate, number of neurons, and batch size, were tuned through cross-validation to ensure optimal performance. The ANN models were evaluated both for short-term prediction tasks and for minimizing residual error following clock ensemble averaging.

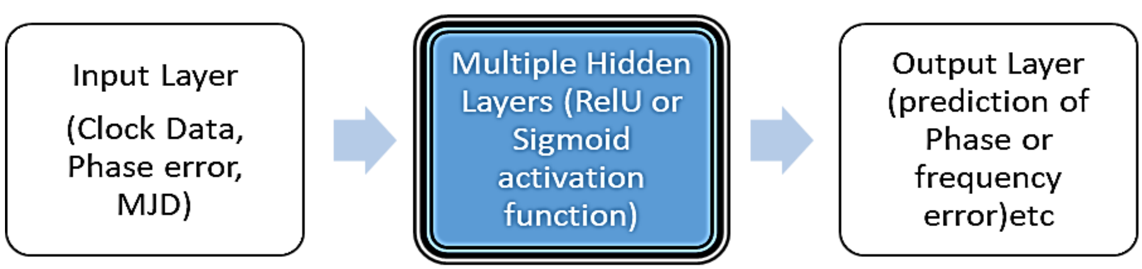

FIGURE 6.1 ANN ARCHITECTURE FOR TIMESCALE DEVELOPMENT

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6.2.2. AutoRegressive Integrated Moving Average (ARIMA)

ARIMA (AutoRegressive Integrated Moving Average) is a widely used statistical model for analyzing and forecasting time series data. Its primary objective is to predict future trends and uncover underlying patterns within a dataset. The model combines autoregression, differencing, and moving averages to generate accurate forecasts. The autoregressive (AR) component accounts for temporal correlations by expressing the current value as a linear combination of past observations. Differencing (I) is applied to stabilize the mean of the series by removing trends and seasonality, ensuring stationarity. The moving average (MA) component captures the influence of past forecast errors, smoothing predictions based on previous deviations.

Optimal ARIMA model performance depends on careful selection of its three key parameters: p, d, and q. The autoregressive order (p) determines the number of lagged observations included in the model. The differencing order (d) specifies how many times the series must be differenced to achieve stationarity. The moving average order (q) indicates the number of lagged forecast errors incorporated to improve smoothing. Parameter selection is typically guided by techniques such as grid search, the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and cross-validation to ensure reliable and accurate forecasts. Due to its flexibility and effectiveness in capturing complex temporal patterns, ARIMA is extensively applied in sectors requiring precise forecasting, including finance, economics, and inventory management.

6.2.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Through the utilization of a single framework, the Adaptive Neuro-Fuzzy Inference System (ANFIS), which is a hybrid intelligent system, combines the advantages of neural networks with fuzzy logic. ANFIS utilizes both fuzzy logic reasoning principles and neural network learning capabilitiesto simulate complex nonlinear systems. This allows for much more accurate simulations. It is sometimes referred to as a universal estimator because of its ability to approximate a wide variety of functions. This ability derives from the adaptive learning method that it employs. ANFIS is designed in a manner that is analogous to that of a layered neural network, with each layer being responsible for a different set of tasks that are related to fuzzy judgment, as shown in Fig. 6.2. These layers often include the production of output, the normalization of output, the application of rules, the fuzzification of input, and the defuzzification of input. During the training phase, the system's parameters, including membership functions, rule sets, and consequent parameters, are optimized using learning methods such as backpropagation or hybrid approaches.

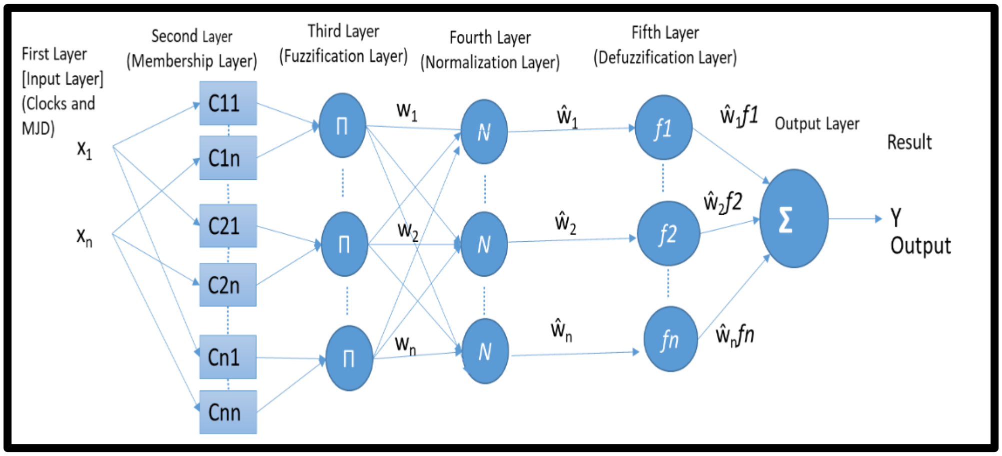

FIGURE 6.2 LAYERED ARCHITECTURE OF ANFIS MODEL

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6.2.4. Support Vector Machines (SVM)

Support Vector Machines (SVMs) were employed for classification tasks and for regression through Support Vector Regression (SVR). In SVR, a regularized hinge-loss
51 function is minimized to achieve a balance between model complexity and predictive accuracy. The study considered the following SVR kernel functions for evaluation:

- Linear: For performance at the baseline level
- 13 For non-linear correlations in time-series clock characteristics, the Radial Basis Function (RBF) is the method of choice.
- The support vector machine (SVM) was utilized to forecast future frequency or phase values, as well as to categorize clocks as normal or abnormal based on the deviation patterns they exhibited. Utilizing grid search with cross-validation, hyperparameters like the penalty term (C) and kernel width (γ) were fine-tuned to achieve optimal performance

SVM was applied to predict future frequency or phase values and to classify clocks as normal or anomalous based on their deviation patterns. Hyperparameters such as the penalty term (C) and kernel width (γ) were tuned using grid search with cross-validation

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6.2.5. Random Forest (RF)-Weighted Timescale

Random Forests, an ensemble method comprising decision trees trained on bootstrapped datasets and employing random feature selection, were utilized to provide dynamic weights to individual atomic clocks according to their recent performance. Each tree forecasted clock stability parameters (*e.g.*, Allan variance, residual error), and the ensemble output was utilized to assess clock quality. The procedure is as follows:

- Feature Extraction: Metrics of clock noise, previous prediction inaccuracies, and environmental variables
- Training: Trees developed to forecast clock deviation or dependability metrics
- Clocks with superior anticipated stability were assigned bigger weights in the ensemble timescale

This system facilitated real-time adaptability, with weights constantly adjusted according to new clock data. RF-weighted timeframes demonstrated enhanced resilience to outliers and suboptimal clocks in comparison to fixed-weight or equal-weight averaging techniques.

6.3. Model Training and Validation

The data entered into the model included readings from eight distinct atomic clocks and the Modified Julian Date (MJD). The clock data was averaged for every MJD to provide a single dataset for additional examination. Comparing the timeframe outputs produced by conventional weighted average techniques with those achieved using advanced AI methods, specifically, ARIMA and ANFIS modeling are the main objective. While weighted averaging is the foundation of the CSIR-NPL's current timing algorithms, AI-based methods are being investigated to improve the precision and stability of timekeeping. The current weighted average methodology is not adaptive as per the behavior of that clock. This method might not, however, adequately capture the intricate connections and non-linear patterns that develop over time between several clocks. However, AI models like ARIMA and ANFIS can learn adaptively from past clock data and produce a more accurate timescale representation.

6.3.1. ARIMA Modelling

To commence the development of an ARIMA model, collection, and pre-processing of several time series datasets, "clock statistics" data is collected here. Refer

133 113 32

to Fig.3 for the processing steps in ARIMA modelling. This heterogeneous collection of datasets acts as the fundamental input for the model. After obtaining the input data, a comprehensive analysis of its features, including trends, seasonality, and associated patterns, is done. The significance of this study is in its ability to direct towards identifying a particular ARIMA model that closely corresponds to the distinctive characteristics of the dataset. In the identification procedure, the objective is to ascertain the suitable sequence of the autoregressive (AR) and moving average (MA) components, together with the necessary level of differencing to attain stationarity in the time series.

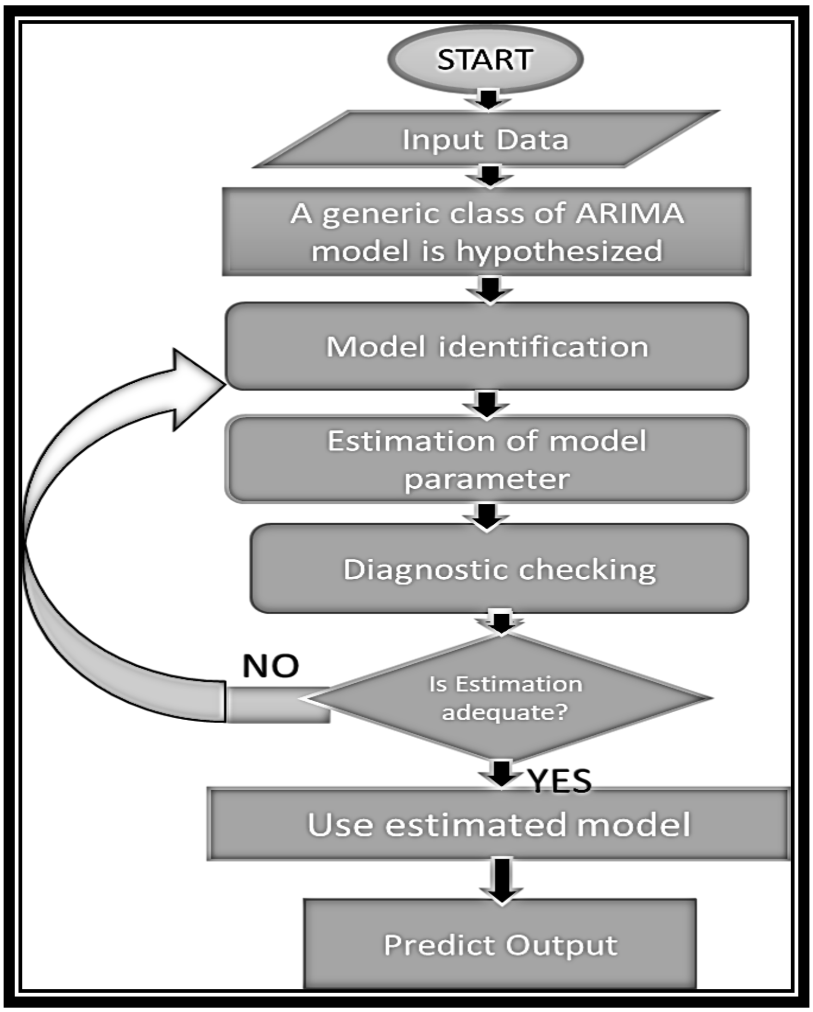

FIGURE 6.3 FLOWCHART FOR ARIMA MODELLING

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After selecting an appropriate ARIMA model, key parameters—including the autoregressive (AR) and moving average (MA) coefficients, along with the differencing

149 order—are estimated. Diagnostic checks are then performed to assess model adequacy, primarily by analysing the residuals for characteristics of white noise, such as the absence of autocorrelation and constant variance. If the residuals meet these criteria, the model is deemed suitable for forecasting future values using new data. If diagnostic analysis indicates issues, such as systematic patterns in the residuals or poor fit, the modelling process returns to the identification stage. At this point, alternative ARIMA specifications are explored, parameters are recalculated, and model assumptions are reassessed. This iterative approach ensures the development of a robust and reliable
27 ARIMA model that accurately captures the underlying dynamics of the time series, enabling dependable forecasting.

6.3.2. ANFIS Modelling

61 In designing the ANFIS model, the dataset is partitioned into two subsets: 80% is allocated for training, while the remaining 20% is reserved for testing, as illustrated in Fig. 6. 4. This division ensures that the model has sufficient data to learn underlying patterns and relationships without being overwhelmed, while also allowing for an independent assessment of its performance. The process begins by loading the training dataset, which serves as the primary input for the ANFIS model. This dataset provides essential information for the system to learn and adjust its parameters effectively. The next step involves selecting appropriate membership functions, a critical component in fuzzy logic that determines how input data is interpreted according to linguistic criteria. The choice of these functions directly impacts the model's accuracy and computational
13 efficiency. During training, the model's learning performance is continuously evaluated using the training dataset. Upon completion of the training phase, the outcomes are
5 assessed to gauge the model's performance and identify areas for potential improvement, ensuring that the ANFIS system achieves optimal functionality.

55 During the training phase of the ANFIS model, if the process is incomplete, the system returns to the input stage to continue processing the remaining data. This iterative procedure persists until the entire training dataset has been successfully analysed. Upon completion of training and evaluation of the results, the focus shifts to the testing phase.

In the testing phase, the remaining 20% of the dataset, previously set aside, is used as input for the ANFIS model.

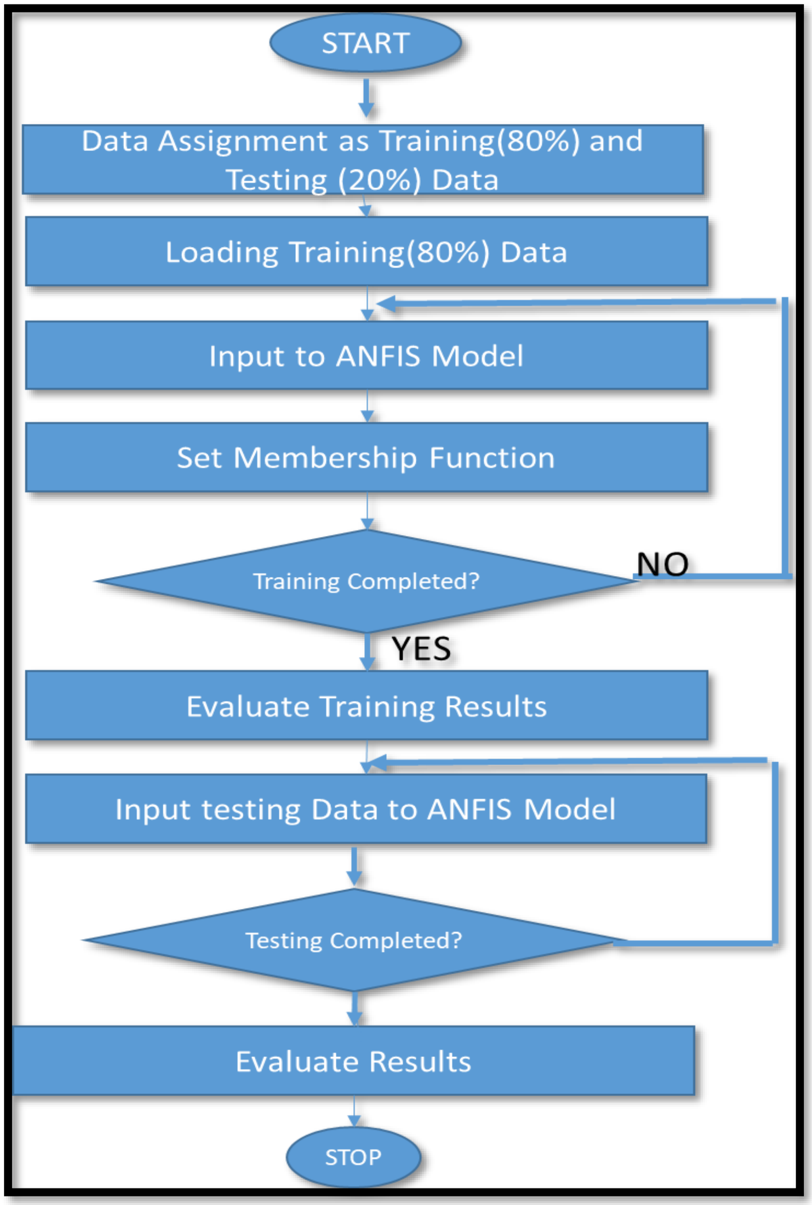

FIGURE 6.4 FLOWCHART FOR ANFIS MODELLING WITH TRAINING OR MODELLING AND TESTING PHASE OF DATA

The system ensures that all test data points are processed, and the results are subsequently assessed. This evaluation is critical for gauging the model's generalization capability and its performance on previously unseen data. Should any data points remain unprocessed, the model revisits the input stage, continuing the cycle of testing and assessment until all datasets have been fully examined. This systematic approach ensures the robustness and reliability of the ANFIS model, enabling precise and meaningful results across diverse applications.

While ARIMA is suitable for time series forecasting and handling temporal dependencies, ANFIS leverages the combination of neural networks and fuzzy logic to address nonlinearity and uncertainty in clock data. The study evaluates improvements in stability, accuracy, and consistency by comparing outputs from various AI algorithms with conventional methods. Furthermore, the analysis assesses the models' performance in managing drifts, noise, and abrupt variations in clock behaviour. Within the ANFIS framework, specific parameters are employed to enhance analytical precision and effectiveness. The model is based on the Sugeno-Fuzzy Inference System, which is well-suited to handle complex, data-driven problems due to its ability to manage uncertainty and imprecision. Gaussian membership functions represent the fuzzy sets in this framework, providing smooth, bell-shaped curves that allow for refined data characterisation and effective handling of fluctuations.

The ANFIS training process utilises the Backpropagation algorithm, optimising network parameters to minimise discrepancies between predicted and target outputs. The model is trained over 5000 epochs, allowing gradual improvement in prediction accuracy and generalisation. An error tolerance of 0.0001 is set to control convergence, ensuring a balance between training duration and model performance, and enabling high-precision outcomes. The linear output function establishes a direct relationship between input variables and output predictions, maintaining interpretability while effectively capturing fundamental data patterns. These factors collectively establish a strong framework for efficiently evaluating intricate datasets.

6.3.3. Machine Learning Modelling: SVM and RF

For all machine learning models, the input feature set (X) consisted of raw signals from multiple atomic clocks at each time interval, augmented with engineered statistical and temporal descriptors. Rolling features—including mean, standard deviation, median, minimum, maximum, and peak-to-peak values—were computed over sliding windows of (3, 7, 14) samples to capture short- to medium-term stability trends. Delta features, such as first differences and rolling slopes, were included to characterize drift dynamics, while spectral proxies, including Welch-band energy in the low-frequency range, were employed to analyze noise behavior. Health indicators, such as recent percentages of missing data and outlier occurrences, were incorporated to downweight unreliable sources. Additionally, temporal context was optionally represented using cyclical encodings of weekly patterns to provide information on recurring trends.

The prediction target (y) was established as the composite stability estimate of the timescale, synchronized with the cadence of the input signals. A time-sensitive forward chaining cross-validation method with five folds was utilized for assessment, succeeded by a final held-out test period. To prevent leakage, preprocessing procedures like scaling and encoding were exclusively applied to training folds and subsequently extended to validation and test sets. Model optimization focused on minimizing root mean squared error (RMSE), whereas mean absolute error (MAE) and coefficient of determination (R^2) served as additional metrics. In instances of comparable validation performance, stability metrics, specifically Allan deviation at average times $\tau \in \{1, 2, 5, 10, 20, 30\}$ days and the suppression of low-frequency power spectral density (PSD) were employed as tiebreakers to identify the optimal models.

6.3.3.1. SVM Modeling

The optimal SVM framework for timeline generation was determined to be the Support Vector Regression (SVR) model with a radial basis function (RBF) kernel, implemented using scikit-learn. The model was encapsulated in a pipeline that included StandardScaler to normalize continuous features, with scalers applied solely to training folds to avert data leaking. Preprocessing involved linear imputation for brief missing intervals, whereas extended gaps were either excluded or marked with health indicators. Following cross-validation, the selected hyperparameters were: kernel = RBF, C = 100, ϵ = 0.1, γ = scale, tolerance = 10^{-3}, maximum iterations = 100,000, and cache size = 200 MB. Hyperparameter optimization was conducted utilizing GridSearchCV and RandomizedSearchCV with a five-fold TimeSeriesSplit, exploring the following parameter ranges: $C \in \{ 0.1 , 1 , 10 , 100 , 1000 \}$ C∈{0.1,1,10,100,1000}, $\epsilon \in \{ 0.001 , 0.01 , 0.1 , 0.5 , 1.0 \}$ ϵ∈{0.001,0.01,0.1,0.5,1.0}, and $\gamma \in \{ \text{scale} , \text{auto} , 10^{-4} , 10^{-3} , 10^{-2} , 10^{-1} \}$ γ∈{scale, auto, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}}.

39 A total of 50 candidate configurations were assessed, with the optimization goal of minimizing the negative root mean squared error (RMSE). In contrast to neural models, the SVR does not undergo training in epochs but rather optimizes iteratively until convergence or until the iteration limit is reached. The model's performance was evaluated on the reserved test set utilizing RMSE, mean absolute error (MAE), and the coefficient of determination (R^2). Furthermore, stability was assessed via power spectral density (PSD) analysis employing Welch's method and Allan deviation over averaging durations $\tau \in \{1, 2, 5, 10, 20, 30\}$ days. Ultimately, disparities compared to a basic equal-weight average baseline were assessed, illustrating the advantages of SVM-optimized timeframes in terms of predicted accuracy and long-term stability.

6.3.3.2. Random Forest Modelling:

Scikit-learn's RandomForestRegressor generated weighted timelines for the Random Forest (RF) model. During training, a 30-day exponential time decay weighting scheme was used to emphasise recent observations. Cross-validation determined the final hyperparameters: n_estimators = 600, maximum depth = 14, minimum samples per split = 4, minimum samples per leaf = 2, parallel execution across cores(n_jobs=-1), and random state = 42. The hyperparameter search space examined candidate values for tree number (300-1000), maximum depth (8,12,14,16,20), split thresholds (2, 6, 8), leaf sizes (1, 2, 4) and feature selection schemes (sqrt, log2, 0.5) was used. The RandomizedSearchCV technique with a five-fold TimeSeriesSplit evaluated 60 candidates and training complexity was determined by the number of trees and their depth, with a budget of 600 n_estimators. Evaluation included RMSE, MAE and R^2 on the held-out test window, along with stability analysis using Welch PSD and Allan deviation over $\sim\tau \in \{1,2,5,10,20,30\}$ days. In comparison to a simple equal-weight averaging baseline, RF weighting reduced long-term drift and improved low-frequency noise suppression.

6.3.3.3.Combined SVM-RBF with RF

A mixed model using SVM (RBF) and RF Weighted predictors was created to combine the strengths of kernel-based and ensemble-based techniques. Convex mixing was used in the combination as given in Eq.6.1:

$$\hat{y} = w_{\{svm\}} \cdot \hat{y}_{\{svm\}} + w_{\{rf\}} \cdot \hat{y}_{\{rf\}} \quad (6.1)$$

where $w_{\{svm\}} + w_{\{rf\}} = 1$, $w_{\{svm\}} \in \{0.0,;\ 0.05,;\ 0.10,;\ 0.95,;\ 1.0\}, w_{\{rf\}} = 1 - w_{\{svm\}}$, and final weights would be, $w_{\{svm\}} = 0.4,\ w_{\{rf\}} = 0.6$.

This indicates the RF component's greater long-term noise reduction while maintaining the SVM model's anomaly sensitivity. Alternatively, a stacking ensemble with nonnegative RidgeCV regression confined to sum-to-one weights was tested, but the convex blend performed well and was interpretable. Evaluation metrics, including RMSE, MAE, and R^2, were calculated on the test window, together with PSD and Allan deviation diagnostics. During training iterations, the maximum iteration limit (10^5) and tolerance (10^{-3}) were used to manage SVR optimization progress. Training complexity for Random Forest was determined by the number of trees (n_estimators=600) and maximum depth (14). Cross-validation iterations are the number of hyperparameter trials evaluated- 50 for SVM and 60 for RF, in their search algorithms.

6.4. Results

The models for ARIMA and ANFIS were designed for all the clocks. Their performance is assessed based on parameters of Mean Absolute Deviation (MAD), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Equations used in the results are given in Eq. 6.2 to 6.4.

6.4.1 MAD

Measures the average magnitude of forecast errors, regardless of their direction. MAD measures absolute error, so positive and negative errors don't cancel each other out. MAD has some advantages, such as providing a precise measure of the average error magnitude and being insensitive to the direction of errors. Equation 1 gives the formula for MAD. However, it doesn't provide insights into over- or under-forecasting and can be sensitive to outliers.

$$y = 1/n \sum_{i=1}^{n} |xi - m(X)| \quad (6.2)$$

where m(X) is the average value of the data set, n is the number of data values in the data set, and xi is the “i”th data value in the set.

6.4.2 RMSE

Measures the variance of forecast error. MSE is considered the preferred forecast error measure by Eq. 6.2.

$$y= \sqrt{\frac{\sum(Xi-\hat{X}_i)^2}{N}}(6.3)$$

where x_i are the observed values and $\hat{x}_i$ are the predicted values in the data set having total of N data points.

6.4.3 MAPE

Measures absolute error as a percentage of the forecast to calculate using Eq. 6. 3. *e.g.*, a 20% MAPE would be entered as 0.2

$$y \ = \frac{1}{n}(\sum_{i=1}^{n} | \frac{x_i-x\hat{i}}{x_i} |) * 100(6.4)$$

6 where xi is the actual observation, and xi is the predicted value of sample size n.

6.4.4. Results of ARIMA and ANFIS Modelling

Table 6.1 shows the results. The ARIMA model of AHM 01 yields a Mean Absolute Deviation (MAD) value of 2.03, which is higher than the MAD value of 1.38 obtained with ANFIS modelling in training mode. Nevertheless, the identical clock yields a MAD score of 36.39 in ARIMA testing and a value of 0.85 in ANFIS testing. The ANFIS model is highly advanced.

TABLE 6.1 SUMMARY OF ARIMA AND ANFIS MODELLING FOR ALL CLOCKS DATA

Data Type	Model	Training			Testing		
		MAD	RMSE	MAPE	MAD	RMSE	MAPE
AHM 01	ARIMA	2.0370	4.0020	0.0365	36.3935	43.2595	0.5440
	ANFIS	1.3898	4.1492	0.0243	0.8545	1.0832	0.0128
AHM 02	ARIMA	0.8233	1.7520	0.0773	11.4028	13.1047	0.8189
	ANFIS	0.3836	0.8371	0.0356	0.4812	0.5311	0.0347
Clock 02	ARIMA	2.7273	3.5388	0.0379	46.5853	55.6574	0.6376
	ANFIS	2.6365	3.1809	0.0367	2.2359	2.7883	0.0307
Clock 08	ARIMA	22.5654	36.0676	0.0344	324.4659	364.7372	0.4874

Data Type	Model	Training			Testing		
		MAD	RMSE	MAPE	MAD	RMSE	MAPE
	ANFIS	23.5677	35.1237	0.0358	9.7875	9.9232	0.0147
Clock 09	ARIMA	1.2506	1.5622	0.0269	3.6033	3.9405	0.0770
	ANFIS	0.4943	0.7241	0.0106	1.3912	1.6360	0.0297
Clock 10	ARIMA	0.9641	1.2460	0.0166	12.9392	14.6627	0.2089
	ANFIS	0.3928	0.5644	0.0067	9.7407	11.1170	0.1573
Clock 11	ARIMA	1.0161	1.4797	0.0935	8.4846	9.7570	0.6523
	ANFIS	0.1773	0.2862	0.0154	2.2977	2.5780	0.1781
PHM 02	ARIMA	0.9504	1.2169	0.1282	8.8639	10.2121	1.2091
	ANFIS	0.7986	1.0293	0.1075	3.3709	4.7401	0.4556

The ARIMA training for AHM 02 yields a Mean Absolute Deviation (MAD) of 0.82, when tested it increases to 11.4. The Mean Absolute Deviation (MAD) in ANFIS modelling is 0.38 during training and 0.48 during testing. Furthermore, other clocks also exhibit comparable performance. Nevertheless, based on the aforementioned modelling, it is pretty clear that clock 08 is operating sporadically. Training yields a Mean Absolute Deviation (MAD) value of 22.56, which increases to 324.4 during testing. The root mean square error (RMSE) values are consistently remarkably high, namely 36.06 in training and 364.7 in testing. The ANFIS modelling analysis reveals no significant difference between the MAD value of 23.56 and RMSE of 35.12 in testing and training, and the MAD of 9.78 and MSE of 9.92. These findings indicate the effects of clock ageing, ambient conditions, or other variables. These factors will harm the calculation of the timescale when averaging all clock data. A comparison is made between the Timescale obtained using these clocks and the models of ARIMA and ANFIS. The results of this comparison are presented in Fig. 6.5. The overall graph exhibits a significant degree of overlap between the original data and the models. A comprehensive examination of the results can be focused on in the three sections labelled A, B, and C.

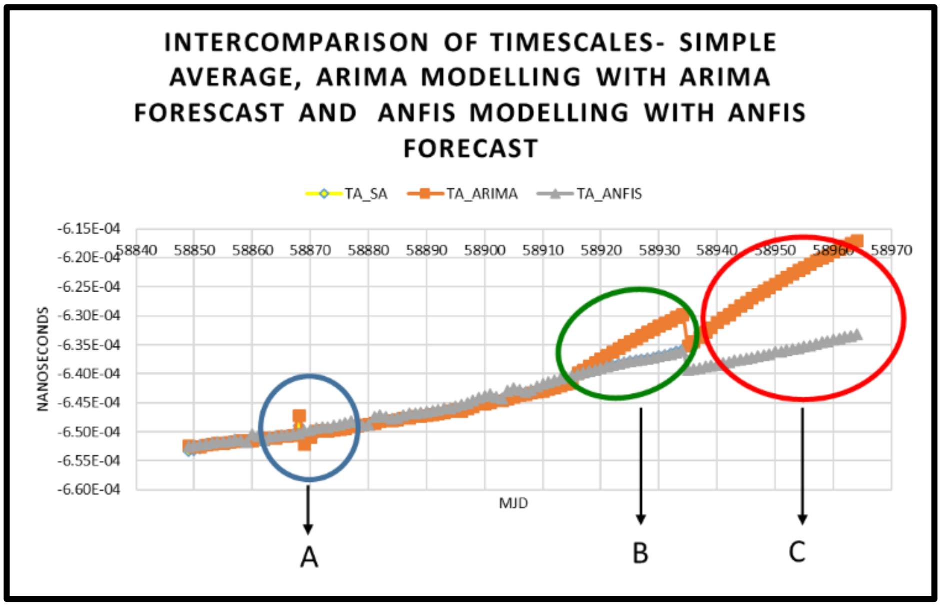

FIGURE 6.5 INTER-COMPARISON OF TIMESCALE WITH A SIMPLE AVERAGE OF CLOCK DATA, WITH THAT OF ARIMA MODELLING AND ORECASTING, AND ANFIS MODELING AND FORECASTING

Section A reveals data abnormalities around MJD 58870, evident in the TA_SA (Simple average timescale) and TA_ARIMA (Timescale with ARIMA shaping). However, the TA_ANFIS timeframe, which incorporates ANFIS modelling, is the least impacted by these anomalies. It serves as the training segment until the beginning of the B section. Section B presents the testing findings obtained following data modelling using ARIMA and ANFIS. The presence of anomalies in the modelling part causes the ARIMA timescale to shift higher. Nevertheless, TA_ANFIS consistently produces highly reliable benchmark results. Section C displays a 30-point lead above the sample forecast made by ARIMA and ANFIS models. The forecast drift of the ARIMA model remains unchanged from the testing phase. Indeed, the ANFIS forecast exhibits remarkable stability with minimal deviation. Therefore, it can be asserted that TA_ANFIS has established a reliable timeframe even in the presence of data abnormalities. The outcomes may demonstrate further improvement if these abnormalities are addressed early. The investigation revealed that Clock 08 exhibited the highest level of instability. Thus, the data for this clock underwent pre-processing to eliminate any outliers. The results obtained by eliminating the outliers from the clock 08 data are presented in Table 6.2.

Table 6.2 SUMMARY OF ARIMA AND ANFIS MODELLING OF CLOCKS DATA SET OF CSIR-NPL AFTER REMOVING THE OUTLIER OF CLOCK 08.

Data Type	Model	Training			Testing		
		MAD	RMSE	MAPE	MAD	RMSE	MAPE
AHM 01	ARIMA	2.0370	4.0020	0.0365	36.3935	43.2595	0.5440
	ANFIS	1.3898	4.1492	0.0243	0.8545	1.0832	0.0128
AHM 02	ARIMA	0.8233	1.7520	0.0773	11.4028	13.1047	0.8189
	ANFIS	0.3836	0.8371	0.0356	0.4812	0.5311	0.0347
Clock 02	ARIMA	2.7273	3.5388	0.0379	46.5853	55.6574	0.6376
	ANFIS	2.6365	3.1809	0.0367	2.2359	2.7883	0.0307
Clock 08	ARIMA	22.5654	36.0676	0.0344	324.4659	364.7372	0.4874
	ANFIS	23.5677	35.1237	0.0358	9.7875	9.9232	0.0147
Clock 08 (New)*	ARIMA	6.4790	7.9702	0.0098	5.3021	6.1801	0.0080
	ANFIS	4.9701	6.4789	0.0076	1.2901	1.6727	0.0019
Clock 09	ARIMA	1.2506	1.5622	0.0269	3.6033	3.9405	0.0770
	ANFIS	0.4943	0.7241	0.0106	1.3912	1.6360	0.0297
Clock 10	ARIMA	0.9641	1.2460	0.0166	12.9392	14.6627	0.2089
	ANFIS	0.3928	0.5644	0.0067	9.7407	11.1170	0.1573
Clock 11	ARIMA	1.0161	1.4797	0.0935	8.4846	9.7570	0.6523
	ANFIS	0.1773	0.2862	0.0154	2.2977	2.5780	0.1781
PHM 02	ARIMA	0.9504	1.2169	0.1282	8.8639	10.2121	1.2091
	ANFIS	0.7986	1.0293	0.1075	3.3709	4.7401	0.4556

The MAD in ARIMA significantly increases from 22.56 to 6.4790 during training and from 324.46 to 5.30 during training. In the ANFIS model, the MAD improves from 23.58 to 4.97 during training and 1.2 from 9.78 during testing. As mentioned earlier, the adjustments that enhance the performance of the Timescale ensemble even further are illustrated in Fig. 6.6.

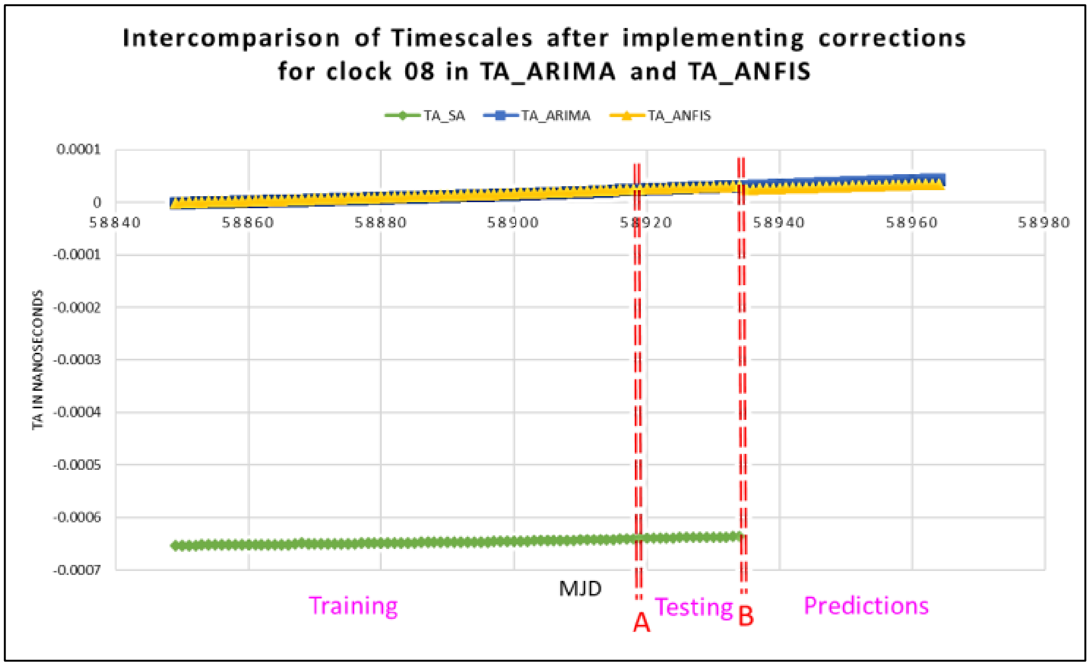

FIGURE 6.6 INTER-COMPARISON OF TIMESCALE WITH A SIMPLE AVERAGE OF CLOCK DATA, WITH THAT OF ARIMA MODELLING AND FORECASTING AND ANFIS MODELLING AND FORECASTING AFTER CORRECTING FOR CLOCK08

According to Fig. 6.6, the ARIMA and ANFIS models yield an enhanced timescale that is two orders superior to the simple average timescale. Based on the training model up to point a, it is clear that data anomalies around MJD 58870 have been eliminated in this study because corrections have been made for the corresponding clock 08. TA_ARIMA, which stands for timescale with ARIMA modelling, and TA_ANFIS, denoting timescale with ANFIS modelling, remain unaffected by these anomalies. The a-b segment is exclusively dedicated to training. Section b presents the testing findings obtained following data modelling using ARIMA and ANFIS. Pre-processing of the data facilitates the production of a smooth timeline with minimal drift during the testing phase. The presence of anomalies in the modelling part causes the ARIMA timescale to shift higher. Nevertheless, TA_ANFIS consistently produces highly reliable benchmark results.

Graph after point B refers to a sample prediction that is 30 points ahead of the actual value obtained by ARIMA and ANFIS models. Once again, the ARIMA prediction drift precisely corresponds to the testing phase drift. Indeed, the ANFIS forecast exhibits remarkable stability with minimal deviation. Hence, it may be asserted that TA_ANFIS has established a reliable timescale.

6.4.5. Evaluation of Long-Term and Short-Term Stability of ARIMA and ANFIS Timescale with that of Traditional Methods

Short-term and Long-term stability were also assessed for the ARIMA and ANFIS models, compared with the Kalman and simple average timescales. The same is depicted in Fig. 6.7 and 6.8, respectively.

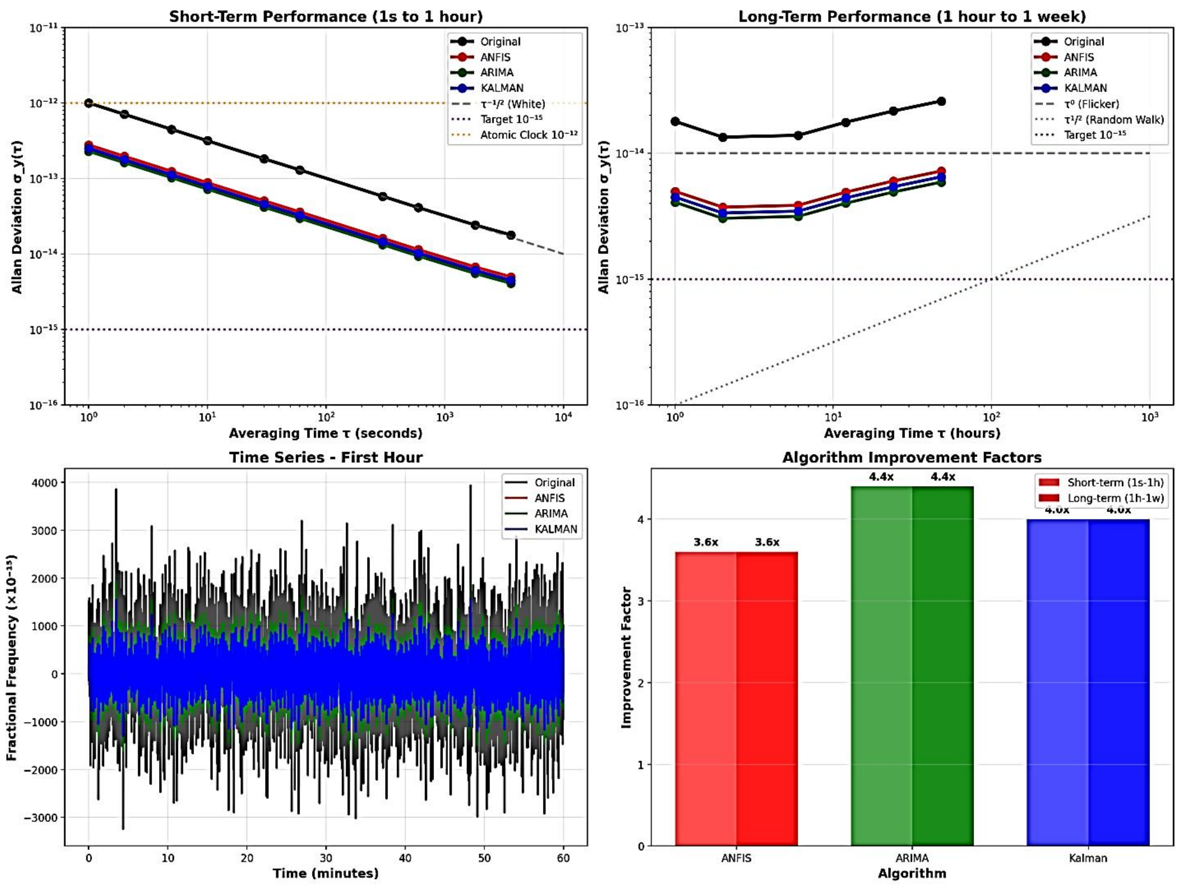

Figure 6.7 Performance comparison of ANFIS, ARIMA, and Kalman filtering for timescale generation. Top left: Short-term Allan deviation (1 s–1 h), showing clear improvements over the original signal.

Top right: Long-term Allan deviation (1 h–1 week), with all algorithms achieving stability well below the original. Bottom left: Fractional frequency time series for the first hour, where filtering significantly reduces fluctuations. Bottom right: Improvement factors, showing that ARIMA and Kalman achieve the highest gains (~4.4× short- and long-term), while ANFIS provides moderate improvement (~3.6×).

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The results demonstrate all ANFIS, ARIMA, and Kalmanconsiderably improve both short- and long-term stability compared to the unprocessed clock signal. In the short-term regime (1 s–1 h), Allan deviation analysis shows that the processed signals approach the theoretical white noise boundary, with ARIMA and Kalman models providing the most significant reductions, achieving improvement factors of approximately 4.4 times. ANFIS, also delivers meaningful improvements of around 3.6 times over the baseline. In the long-term regime (1 h to 1 week), ARIMA and Kalman again outperform, maintaining lower deviations closer to the flicker noise threshold, while ANFIS follows with intermediate performance. The time-series plots further confirm these findings, as the raw clock frequency displays wide fluctuations that are effectively suppressed after model application, particularly with the Kalman filter. Finally, the improvement factor analysis quantitatively validates the superior performance of ARIMA and Kalman over ANFIS across both regimes. Overall, these results highlight the value of combining statistical and AI-based approaches, with ARIMA and Kalman offering the most consistent gains in stability.

6.4.6. Results of SVM RF optimized timescale as a Comparative Analysis of different Timescale generation methods

The comparative performance of the different timescale generation methods, Simple Average, Kalman Filter (KF) Timescale, SVM optimized, and RF Weighted, is illustrated in Fig. 6.7 across multiple stability diagnostics.

The PSD plot (top left) reveals that the RF Weighted timescale consistently exhibits the lowest spectral power at low frequencies, indicating superior suppression of long-term noise. The SVM Optimized and KF Timescale methods perform better than the Simple Average but remain less effective than RF. The Simple Average shows elevated PSD across the entire frequency band, confirming its vulnerability to drift and low-frequency noise. The Allan deviation curves (top right) further highlight the advantage of the RF Weighted method, which achieves the lowest deviations across averaging times $\tau \in [1,30]$days.The SVM Optimized approach provides intermediate improvements, while the KF Timescale reduces short-term instability but diverges for longer averaging times. By contrast, the Simple Average demonstrates significantly higher deviations, particularly at longer intervals, underscoring its inferior long-term stability. The bar chart (bottom left) compares normalized values of Allan deviation, standard deviation, maximum deviation, and peak-to-peak variation on a logarithmic scale. Here, the RF Weighted method consistently achieves the lowest metric values, followed by the SVM Optimized model, indicating better robustness and consistency in stability. The Simple Average again shows the largest instability across all measures, while KF remains an intermediate performer. The difference plot (bottom right) quantifies performance relative to the Simple Average baseline. Both RF Weighted and KF Timescale exhibit consistently higher offsets, with RF showing the most pronounced improvements across the test window. SVM demonstrates smaller but still meaningful deviations, aligning with its intermediate position observed in the stability metrics.

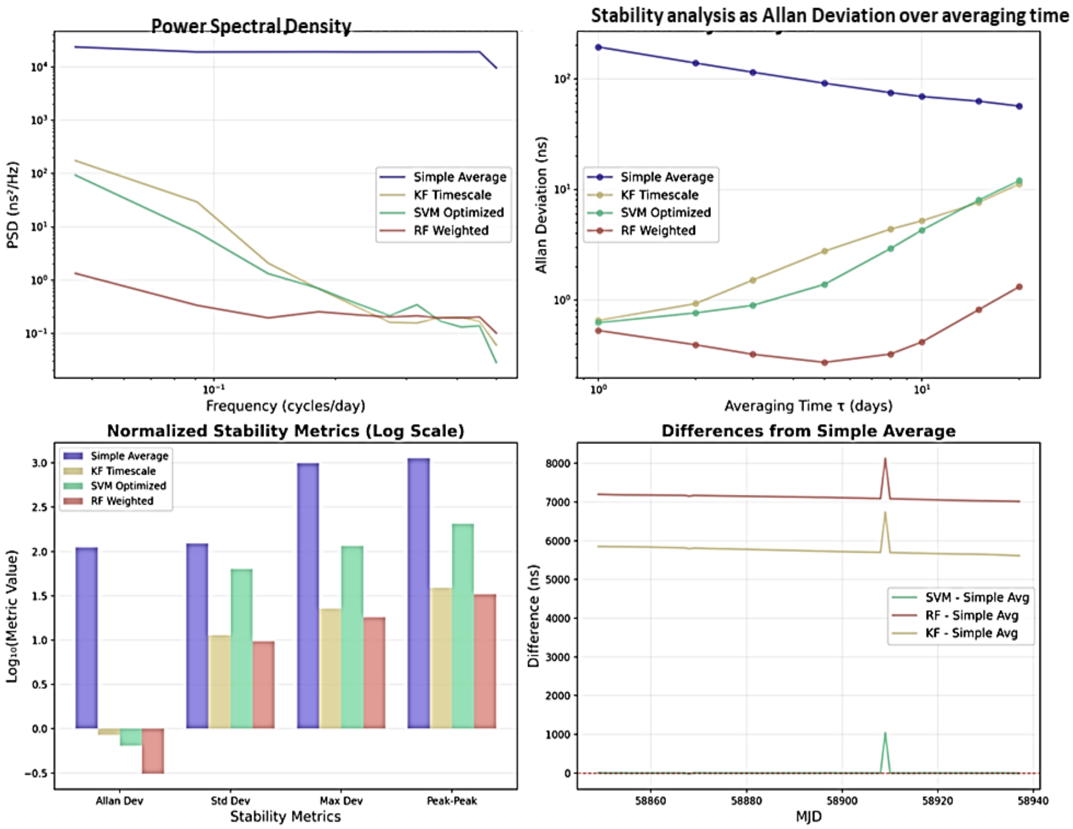


FIGURE 6.8 COMPARATIVE STABILITY ANALYSIS OF TIMESCALE GENERATION METHODS. TOP LEFT: POWER SPECTRAL DENSITY (PSD) SHOWING SUPPRESSION OF LOW-FREQUENCY NOISE, WITH RF WEIGHTED ACHIEVING THE LOWEST SPECTRAL POWER. TOP RIGHT: ALLAN DEVIATION ACROSS AVERAGING TIMES ∈[1,30] DAYS, HIGHLIGHTING SUPERIOR STABILITY OF RF WEIGHTED OVER SVM OPTIMIZED, KF TIMESCALE, AND SIMPLE AVERAGE. BOTTOM LEFT: NORMALIZED STABILITY METRICS (LOG SCALE) COMPARING ALLAN DEVIATION, STANDARD DEVIATION, MAXIMUM DEVIATION, AND PEAK-TO-PEAK VARIATION, WHERE RF WEIGHTED CONSISTENTLY OUTPERFORMS OTHER METHODS. BOTTOM RIGHT: DIFFERENCES FROM THE SIMPLE AVERAGE BASELINE ACROSS MJD, DEMONSTRATING SIGNIFICANT STABILITY GAINS FOR RF WEIGHTED AND MODERATE IMPROVEMENTS FROM SVM AND KF METHODS

6.5.Conclusion

AI-driven models for timescale generation and prediction were evaluated, revealing substantial improvements over conventional statistical techniques. The integration of machine learning models significantly enhanced forecast accuracy, robustness against anomalies, and generalization capacity, addressing critical limitations inherent in traditional methods. Across all models, AI frameworks consistently demonstrated superior dynamic adaptability to clock variations and operational reliability, supporting deployment in precision-critical domains such as defense, banking, and telecommunications.

From a performance standpoint, the Support Vector Machine (SVM) with an RBF kernel emerged as the most effective predictor, achieving an accuracy of R^2=0.9994 and a mean squared error (MSE) of 2.44, establishing a new benchmark for timescale prediction. The Random Forest (RF) model exhibited moderate performance (R^2=0.85), reflecting robustness but reduced sensitivity to subtle clock fluctuations. In contrast, the Simple Average baseline performed poorly, highlighting its inability to accommodate anomalies and the non-stationary behavior of atomic clock ensembles. Sequential SVM models yielded intermediate results, often surpassed by the RBF-SVM variant, emphasizing the critical role of kernel selection in predictive performance.

55 Hybrid approaches, particularly the Adaptive Neuro-Fuzzy Inference System (ANFIS), provided an effective balance between precision and interpretability. ANFIS excelled in handling uncertainty and rule-based reasoning while maintaining strong predictive performance, relatively low data requirements, and rapid training times. These characteristics render ANFIS both technically robust and operationally practical, particularly in contexts where computational efficiency is important.

Overall, the results indicate that AI models surpass conventional statistical methods in both forecast accuracy and operational resilience. While classical techniques such as Kalman filtering remain valuable for structured noise reduction, the evidence strongly supports a transition toward AI-integrated timescale systems. By leveraging machine learning models, including SVMs and hybrid fuzzy-logic frameworks like ANFIS, modern timing systems can achieve enhanced stability, improved anomaly resistance, and greater reliability in real-world applications. This represents a significant advancement in the modernization of timekeeping infrastructure, ensuring that national and scientific standards continue to meet increasingly stringent demands for precision and durability.

Each AIML model contributed distinct advantages: ARIMA provided a strong statistical baseline; ANN modelled nonlinearities and temporal dependencies; ANFIS added interpretability and adaptive fuzzy reasoning; and SVM and RF introduced supervised learning and ensemble-based weighting mechanisms. Together, these AI/ML models formed a comprehensive toolkit for generating accurate, adaptive, and resilient timescales in next-generation timescale system.

Chapter 7

Application in National Timescale Dissemination

Creating a dependable and accurate timescale is merely the initial phase in the larger framework of timekeeping. However, equally important is the distribution of this timescale to end-users in scientific, industrial, defense, and commercial sectors. Time dissemination involves the transfer of standardized timing signals from national or regional timekeeping centers to distributed systems, facilitating synchronization across various scales, from local networks to global infrastructures. As modern society becomes increasingly dependent on accurate timing, dissemination methods need to cater to a wide range of requirements from millisecond-level synchronization necessary for IT networks to the picosecond level precision required by scientific laboratories and financial centers.

This chapter details the national timescale architecture, a structured system used by National Metrology Institutes (NMIs) to generate, manage, and distribute accurate, traceable time and frequency standards.

7.1. Timescale architectures at various leading laboratories

All NMIs keep UTC at the regional level, which is called UTC (name of the NMI), using combination of multiple cesium clocks and send out time and frequency signals to meet the synchronization needs of their own country [117]. Figures 1 to 3 show the different setups used by different NMIs, such as NICT-Japan, NIST-USA, CSIR-NPLI-India, and others, along-with their time scale uncertainties [118]. The same principle is followed, but the way it is done is different. Every country has a different number of clocks. Some of these have PFS, or Cs fountain clocks, like NIST USA. or NICT Japan etc. Such systems are vital for synchronizing telecommunications, power grids, navigation, and scientific operations.

For example, NIST in the U.S. maintains UTC(NIST), derived from a group of exceptionally precise atomic clocks, such as caesium beams and H-masers

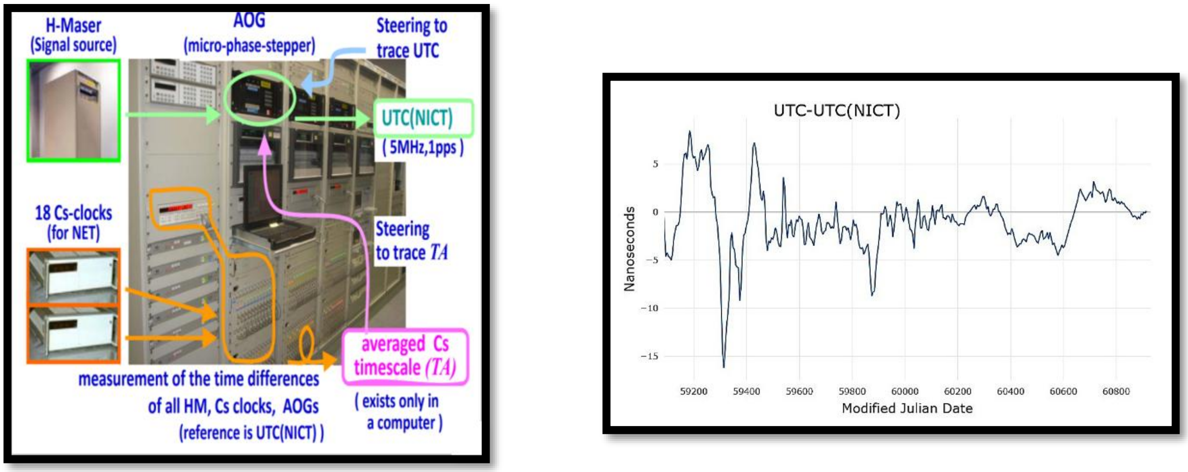


FIGURE 7.1 TIMESCALE SETUP OF NICT-JAPAN

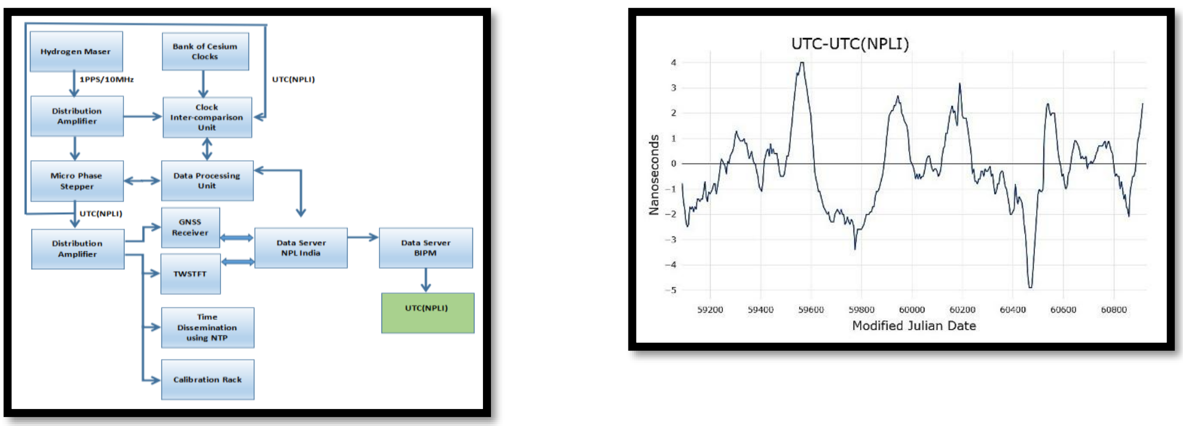


FIGURE 7.2 TIMESCALE SETUP AT CSIR-NPL, INDIA

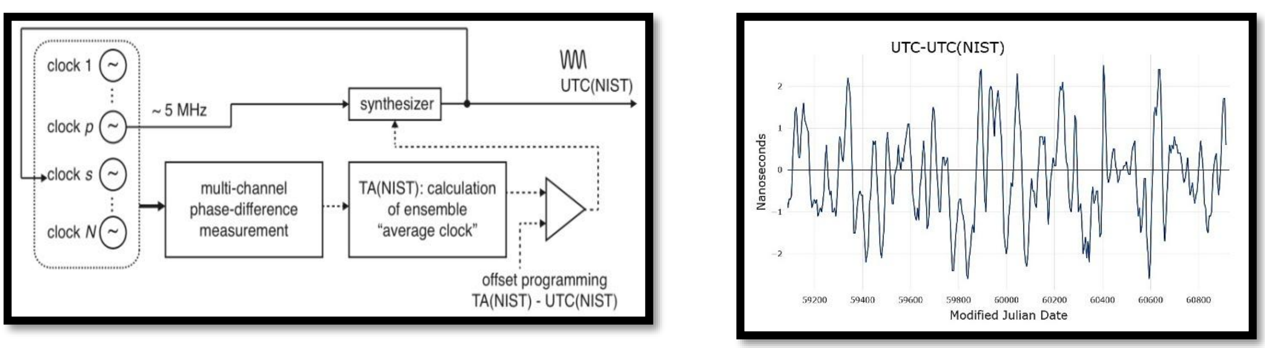


FIGURE 7.3 TIMESCALE SETUP AT NIXT, USA

A real-time algorithm integrates their outputs to produce a stable approximation of Coordinated Universal Time (UTC), continually calibrated against UTC values from the BIPM. NIST disseminates time via radio (WWVB), Internet protocols (NTP/PTP), 9 and Two-Way-Satellite-Time-and-Frequency-Transfer (TWSTFT). Similar architectures exist with various other nations, ensuring national time remains synchronized with UTC and aligned with global timekeeping standards.

7.2. Timescale Dissemination methods

The distribution of standardized timescales serves as the foundation of modern-day synchronization systems. The choice of dissemination methods varies from global satellite-based solutions to localized optical fibre links, depending on the necessary accuracy, coverage, and latency. This section will examine the main dissemination methods, their technical foundations, and their various applications [119].

7.2.1. Dissemination via Satellite

Methods of dissemination that utilize satellites take advantage of orbital platforms to provide extensive coverage with remarkable accuracy. Two primary methods prevail in this category:

7.2.1.1. TWSTFT

This method used geo-stationary satellites to compare remotely located clocks. In TWSTFT system, a pseudo-random code is generated with the help of a modem that is in sync with local clock's 1.0 Hz ticks [120]. This code changes the frequency of a microwave carrier to about 14 GHz, which is the "up-link" frequency. The carrier is then
2 sent to a satellite in geostationary orbit. The satellite sends the modulation back on the "down-link" frequency, which is usually around 12 GHz. The signal gets to the other end, the pseudo-random code is taken out, and a modem turns the code back into 1 Hz ticks by maximizing the cross-correlation of a locally-made copy of the pseudo-random code with the one that was received. The system can send and receive signals at the same time. Usually, the timing accuracy is better than 1 ns.

43

7.2.1.2. Global Navigation Satellite Systems (GNSS)

GNSS include systems like Galileo, GLONASS, BeiDou and GPS that provide time signals on a global scale. These signals facilitate time transfer with an accuracy of tens of nanoseconds, aiding applications in telecommunications, finance, scientific research, and navigation systems. GNSS plays a vital role in synchronizing cellular base stations, data centres, and global trading networks. It is based on common-view method or all-in-view method [121]. In this method, a single source sends time signals to a number of stations. Every station keeps track of when a certain signal gets to its location. Then, the stations compare these numbers and take the difference. If the one-way path delays from the transmitter to the two stations are the same, then the delay and the transmitter's characteristics cancel each other out in the difference. This means that one can figure out the time difference between the two receiving sites without knowing anything about the source or the path delay. Even vicissitudes in the path-delays will be cancelled-out as long as they are the equal for both routes to the two stations.

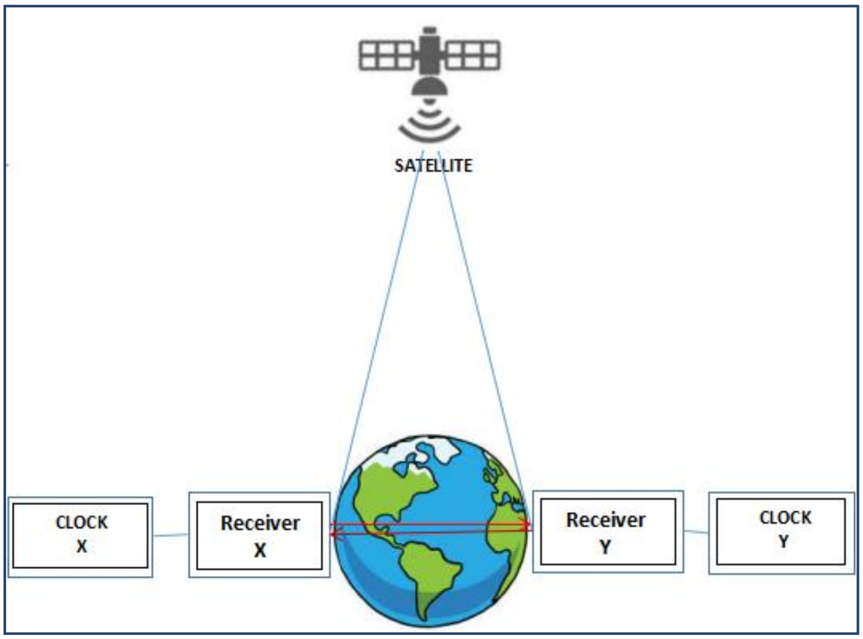


FIGURE 7.4 COMMON-VIEW-GNSS-TIME-TRANSFER-METHOD

Usually, electromagnetic signals and atmospheric paths are used to carry out common-view time transfer (see Figure 3). The need for a clear and easy-to-describe transmission path makes short-wavelength signals the best choice. This is because these signals travel in almost straight lines and can be modelled using the approximations of geometrical optics. Using short wavelengths, on the other hand, makes it impossible to get global coverage from just one transmitter. This problem is solved by the all-in-view method.

One way to achieve global coverage is to use multiple physical transmitters whose signals are synchronized to a common reference. This is the idea behind the "all-in-view" or "melting pot" algorithms. The all-in-view method is especially useful for very long paths, like the one between the US and Australia, because there is no physical transmitter that can be received at the same time at such far-away places.

The GNSS measurements depend on the time difference between the satellite and the reception of pseudo-range-noise (PRN) codes. Figure 7.4 shows the pseudo-range-measurement. One can use the following equation to figure it out:

$$P = c(t_r(rec) - t_e(sat)) \quad (1)$$

Where speed of light is denoted by, “c”.

When the accuracy needed to within sub-microseconds, of the order of nanoseconds, GNSS is the best choice. GNSS is used to sync digital systems with UTC in a number of fields, such as banking, telecommunications, and energy transport and distribution networks.

7.2.2. Internet Time Distribution

The digitalization of infrastructure enables internet-based protocols to offer extensive and scalable access to timing signals.

7.2.2.1. Network-Time-Protocol (NTP)

NTP synchronizes computer system-clocks across TCP/IP networks, achieving accuracy within milliseconds. Although adequate for general IT systems, its precision is limited by network latency and jitter.is very popular method and is widely used [122].

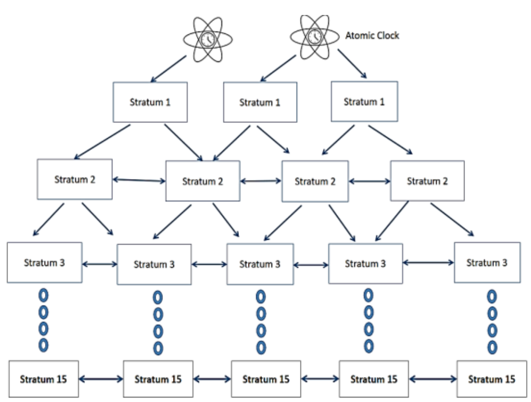


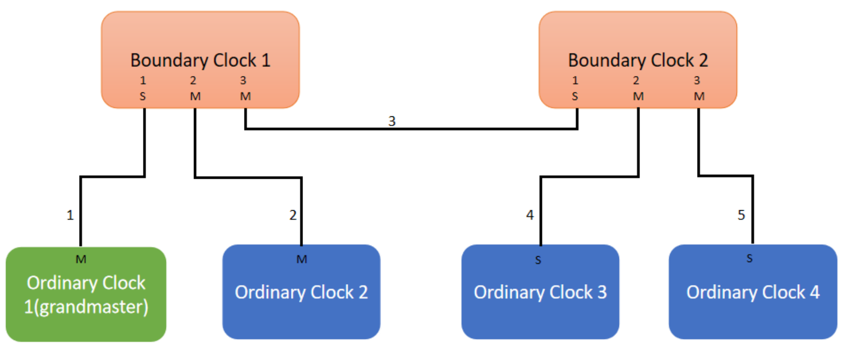
FIGURE 7.5 STRATUM STRUCTURE OF NTP DISSEMINATION

In this method, the client computer initiates a query to the server, and the server sends back timing data in an established format. Client gets information from this data format by changing the network delay to half of the total path delay and syncing its clock.

It continues to be extensively utilized for enterprise systems, server synchronization, and non-essential timing requirements. It's a hierarchical structure as shown in fig.7.5.

99 **7.2.2.2. The Precision-Time-Protocol (PTP, IEEE 1588)**

140 PTP attains accuracy in the microsecond to sub-microsecond range by considering variable delays present in packet-switched networks [123]. In 5G networks, smart grids, high-frequency trading, and industrial automation, the need for tighter synchronization is becoming ever more crucial. To sync a clock across a computer network, PTP is used. It gets the clock accuracy down to less than a microsecond on a LAN, which makes it good for control and measurement systems. PTP has its application
17 in financial transactions, mobile phone tower transmission, and networks that are not connected to satellites but require precise timing. The PTP provides an ordered master and slave Architecture for distributing time and syncing clocks. This hierarchical
2 structure has a time distribution system made up of one or more communication networks and a number of clocks. The same can be referred in Fig.7.6.



2 FIGURE 7.6 HIERARCHICAL STRUCTURE OF PTP TIME SYNCHRONIZATION

An "ordinary-clock" has one networked connection and can be either the master or the slave for the synchronization reference. A boundary clock has more than one connection, and its primary objective is to make sure that one network segment is in sync with another. There are no boundary clocks in a simple PTP network; just regular clocks connected to one network. It is a network of clocks that are set up in a master-slave way.
23 A regular clock has only one network and can be either a source or a receiver. There are 5 types of PTP clock devices: "Ordinary-Clock", "Boundary-Clock", "End-to-end

Transparent-Clock", "Peer-to-peer Transparent-clock" and "Management-Node". PTP guarantees microseconds level time dissemination.

7.2.3. Radio Broadcast Distribution- LF/MF/HF Time Signals

In this method time dissemination is done using Long-wave, medium-wave,and high-frequency broadcasts which delivers time signals across extensive regions [124]. Long-wave radio broadcasts, functioning mainly within the low-frequency band (30–300 kHz), are essential for dependable time dissemination. Their extended wavelengths facilitate ground-wave propagation that closely adheres to the Earth's surface with minimal attenuation, permitting signals to be captured from distances of up to 2000 km away from the transmitter. The stability of long-wave makes it particularly ideal for radio-controlled clocks, as the consistent propagation delay guarantees precise synchronization without the need for intricate adjustments. In comparison to satellite-based systems, long-wave offers benefits like indoor reception, low power consumption, and resilience against obstacles, allowing for compact and cost-effective receivers. Global services such as WWVB in North America and DCF77 in Germany, which are referenced to commercial caesium atomic clocks, deliver timing signals utilized in consumer devices, telecommunications, power grid synchronization, and financial systems. Although contemporary systems such as GNSS provide enhanced accuracy, long-wave broadcasts continue to serve as a valuable complementary option, appreciated for their extensive coverage, durability, and affordability.

7.2.4. Point to Point Time Dissemination Technique

7.2.4.1. White Rabbit Time Dissemination Method

Fiber-Optic Transfer (e.g., White Rabbit-WR): Dedicated optical links facilitate synchronization at the picosecond level, achieving remarkably low latency. The White Rabbit system, created at CERN, showcases the integration of Ethernet with synchronous time transfer. White Rabbit is a technology that is developed by CERN which can provide nanoseconds accuracy for time dissemination. WR disseminates time offering accuracy better of one nano-second and can disseminate frequency with stability better than 10 picoseconds. To achieve this accuracy, the technology utilizes optical filters and standard Ethernet links. The specifications of white rabbit are obtained by the improving different technologies i.e. Precision Time Protocol; used to syncing clock system and the utilization of L1 syncing methodology (encouraged from the "SyncE protocol")

7.2.4.2. Telephone Time Dissemination

One of the easiest and cheapest ways to set the time on a clock from far away is to use time synchronisation over a public switched telephone network [124-125]. A total of 20 NMIs around the world have set up telephone time dissemination. The basic architecture of this technology has a time server at the lab end and receiver modules at the user's end. The time server is linked to the NMI's time scale. The next sections talk about the most important parts of the time synchronisation service offered by NIST in the US, NPL in the UK, NICT in Japan, PTB in Germany, NRC in Canada, and INRIM in Italy. NPL, PTB, and INRIM all use the same data format and transmission scheme as mentioned in Table 7.1 [126]. The Teleclock service has been available at CSIR-NPL in India since 1998[127].

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TABLE 7.1 LEADING NATIONAL METROLOGY INSTITUTES (NMIS) AND THEIR GENERAL-PURPOSE TIME DISSEMINATION SERVICES

NMI (UTC Reference)	Long-Wave / HF Broadcast	Telephone Time Service	NTP Services
NPL, India (UTC(NPLI))	—	*Teleclock*: +91-11-45608687, +91-11-45608688 Accuracy: 10 ms – 1 s	2 active + 19 backup servers Accuracy: ~100 ms
NIST, USA (UTC(NIST))	WWV (60 kHz), Station: Fort Collins, CO Accuracy: —	*ACTS*: +1-303-499-7111 Accuracy: ~30 ms	20 public servers, 3 restricted Accuracy: ~50 ms
NPL, UK (UTC(NPL))	MSF (60 kHz), Station: Anthorn Accuracy: ≤1 ms	TRUETIME: +44-20-8943-6333 Accuracy: ~30 ms	2 NTP servers (internal), 2 NTP servers (public) Accuracy: ~20 ms
PTB, Germany (UTC(PTB))	DCF77 (77.5 kHz), Station: Mainflingen Accuracy: ms-level	+49-0531-512038 Accuracy: few ms	3 servers (public)
NRC, Canada (UTC(NRC))	3330, 7850, 14670 kHz, near NRC Ottawa Accuracy: 0.1 ms	+1-613-745-1576 / +1-613-745-9426 Accuracy: ~1 ms	2 servers (public)
NICT, Japan (UTC(NICT))	LF 40 kHz, 60 kHz, Stations: Ohtakadoya-yama & Hagane-yama	+81-42-327-7592	ntp.nict.jp (public)
NIM, China (UTC(NIM))	BPC (68.5 kHz), Station: Shangqiu	+86-10-6422-9086 Accuracy: ~300 ms	—
Australia (UTC(AUS))	—	+61-2-8467-3727	Multiple servers Accuracy: <10 ms

NMI (UTC Reference)	Long-Wave / HF Broadcast	Telephone Time Service	NTP Services
LNE-SYRTE, France (UTC(OP))	TDF (162 kHz), Station: Allouis (150 km south of Paris) Accuracy: ~1 ms	*Speaking clock*: 4-terminal array Accuracy: ~20 ms	Stratum-1: "ntp-p1.obspm.fr"- (restricted) ; Stratum-2: "ntp.obspm.fr"- (free)
SU, Russia (UTC(RU))	RBU (66.66 kHz), Station: Moscow Accuracy: —	*Speaking clock*: Dial 100 or 060	8 stratum-1 servers + 1 stratum-2 server Accuracy: tens of ms

This dissertation covers application of the timescale to two distinct categories of dissemination: satellite-based transfer utilising the All-in-View method and internet-based dissemination via the Network Time Protocol (NTP). This set of case studies delves into these applications thoroughly, showcasing their performance, the challenges faced during implementation, and their comparative advantages.

7.3. **Case Study -1**

The remote calibration of the "world's largest Gnomon sundial" utilizing "NTP-time-distribution" by CSIR-NPL was taken up as a case study. This section covers, the detailed methodology, procedure, validation techniques and the performance evaluation [128].

7.3.1. Introduction and motivation

For hundreds of years, people from many different cultures have used sundials, which are old-fashioned timekeeping devices that use the position of the Sun to show how time is passing. Sundials need to be calibrated to make sure they are accurate and reliable. This important step involves lining up the dial plate and gnomon so that they correctly show the time of day. GNOMONIC sundials are a special type of sundial because they are beautiful, scientifically accurate, and deeply connected to the stars and planets around us. These clocks, with their interesting shapes and ability to show the passage of time, still fascinate us today. The calibration of sundials is important from a historical point of view and is still of interest to researchers, horologists, and fans alike.

The Maharaja of Jaipur-India, "Sawai Jai Singh-II" had interest in the instruments which can measure time accurately [129]. In 18th century, he converted his imagination into reality and made 5 observatories in India. Table 7.2 shows that these five observatories are in different cities: Jaipur, Varanasi, Ujjain, Delhi, and Mathura. The Jantar Mantar was built for astronomy and astrology (Jyotish), but it is also a major tourist attraction and an important historical site for astronomy [130].

TABLE 7.2 THE LOCATIONS AND VARIOUS INSTRUMENTS PRESENT IN VARIOUS OBSERVATORIES

Sr No.	Observatory Name , Year, and Place	Total No. of Instruments at the obsertvatory
1.	Jantar- Mantar, Mathura(1738)	Not recorded
2.	Jantar- Mantar, Varanasi(1737)	7
3.	Jantar-Mantar, Ujjain(1734)	13
4.	Jantar-Mantar, Delhi(1724)	13
5.	Jantar- Mantar, Jaipur(1734)	19

The main goal of calibrating a sundial is to make sure it keeps time accurately and can be traced back to atomic time. To do this, it's necessary to make sure that the dial plate and gnomon are perfectly aligned and then measure it remotely with IST. This alignment makes sure that the gnomon's shadow falls exactly on the hour lines or divisions on the dial plate, which indicates what time it is. When calibrating a sundial, it's important to think about details like where it is placed, the angle and tilt of the gnomon, the shape and layout of the dial plate, and how the Sun's path changes with the seasons. The main goal of calibration is to make sure that the sundial can be traced back to UTC, which is a timekeeping system that accurately measures time and connects to the natural rhythms of the solar system.

For a case study, Janatar Mantar's sundials in Jaipur, Rajasthan were investigated. One of the “world's-largest-sundials” and astronomical instruments are at Janatar Mantar. This paper examines “Narivalaya-Gola-Yantra”, “Laghu-Samrat-Yantra”, and “Varhat-Samrat-Yantra”. These gadgets measured time for Raja Sawai Jai Singh-II. Time measuring methods and precision vary by instrument. The study measures performance and traceability of these instruments with the Indian Standard Time or IST.

This research's main purpose is to measure Janatar Mantar's sundials' accuracy to ensure they accurately represent Indian Standard Time and provide tourists and enthusiasts with reliable timekeeping information.This study emphasizes the utilization of contemporary timekeeping technologies, such as "NTP-time-dissemination" services, to authenticate the accuracy and standardization of conventional timekeeping devices, including sundials.So the “Sundial-calibration” is about valuing and protecting these beautiful clocks as well as keeping precise time.

7.3.2. Vrihat Samrat Yantra

The Vrihat-Samrat-Yantra is the biggest sundial in the world.About 27 meters tall. It faces 27 degrees, Jaipur's latitude, as shown in fig.7.7. The north celestial pole is facing the triangular central wall of the device. The angle of the right-angled triangle should correspond to the latitude of the observatory, rendering the inclined wall parallel to the rotation of the Earth. Equator-aligned quadrant arcs that are perpendicular to the sloping wall of the instrument.

Triangular wall in samrat yantra acts as gnomon, with semicircular arch perpendicular to inclined wallThe shadows of the gnomon move in alignment with the equator, covering equal distances in the same time intervals. Jaipur's local time is determined by shadow movement on arcs. At 6:00 AM sundial time, the triangular gnomon shadow can be seen in the upper western quadrant. At noon, the shadow shifts from the western quadrant to the eastern quadrant. The shadow meets the top eastern quadrant at 6:00 PM sundial time. The samrat yantra breaks an hour into four equal halves, each of which stands for 15 sundial minutes. Each part of the 15 minutes is a minute.The minute is broken into ten 6-second sections.The 6-second slot is divided into 3 2-second halves.The “Vrihat-Samrat-Yantra”’s original least count and accuracy are 2 seconds.To extract IST from the “Vrihat-Samrat-Yantra”, use the “Adjustment-Factor”.This correction component takes into account the Earth's orbit around the Sun's ellipticity, the tilt of the Earth's axis of rotation in relation to the orbital plane, and the fact that the sundial's timekeeping is always off by the local meridian. Civil time, on the other hand, only uses one longitude for Indian Standard Time's entire validity.

FIGURE 7.7 VRIHATA SAMRAT YANTRA

7.3.3. Narivalaya Yantra

This is a sundial that works at the equinox. The two round plates are tilted south so that they are aligned to the Earth's equator. Refer fig. 7.8 for actual Nadivalaya Yantra The plates face north and south. Two rods project perpendicularly from the centre of these plates. These rods are also parallel to the axis of the earth. The rod shadows on the circular dial show Jaipur's local time. Between fall and spring equinoxes, the south-facing plate tells time because sunlight hits it.Between spring and autumn equinox, the north-facing dial plate displays the time.

FIGURE 7.8 NADIVALAYA YANTRA

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The Narivalaya yantra has 24 equal spaces, each representing 1/2 hour.Half-hour intervals are broken into 12 2.5-minute sessions. This 2.5-minute slot is divided into 5 equal 30-second pieces. Thus, the Narivalaya Yantra accurately displays Jaipur's local time within 30 seconds. To get IST, you need a variance factor, just like the "Varahat-Samrat-Yantra". This correction factor takes into account the fact that the Earth orbits the Sun in an elliptical path, that the Earth's axis of rotation is tilted with respect to the orbital plane, and that the sundial's timekeeping is always corrected by the local meridian. Civil time, on the other hand, uses only one longitude for the entire validity of IST.

7.3.4. Laghu Samrat Yantra

Laghu Samrat Yantra is smaller version of Varahat Samrat Yantra. This instrument works like varahat samrat yantra, see fig. 7.9 for reference. Only accuracy distinguishes these two. The Varahat Samrat Yantra measures time to 2 seconds, while the little sundial (Laghu Samrat Yantra) measures time to 20 seconds. Each of the 12 equal slots on the miniature sundial represents an hour.

FIGURE 7.9 LAGHU SAMRAT YANTRA

26

One hour is divided into 12 slots. Each slot is 5 minutes. Five minutes are divided into five slots. Each slot is one minute. Each minute has three 20-second slots. Like the "Vrihat-Samrat-Yantra", one needs the rectification factor to get IST. This modification factor takes into account that the Earth's orbit around the Sun is not a perfect circle, that the Earth's axis of rotation is tilted with respect to the orbital plane, and that the sundial's timekeeping is always being corrected by the local meridian. Civil time, on the other hand, only uses one longitude for the whole time that IST is valid.

7.3.5. Methodology for Evaluation-

Remote calibration using NTP synchronization was used as a method for setting up traceability of Sundials. This measurement methodology ensures required accuracy with almost no cost involved and is shown in fig.7.10. CSIR-NPL is having NTP time dissemination service via webpage

3 "*https://www.nplindia.in/clockcode/html/index.php.here time.nplindia.org*".

This portal can be accessed via PC or even via mobiles.

The PC/Laptop should be first synchronized to NTP servers via "time.nplindia.org" to accurately synchronize their system clock. It is advised to synchronize the system every 4/5 minutes. This can be auto-scheduled in system configurations. The webpage of CSIR-NPL is then opened and the measurements are physically recorded for Sundial against IST time [131]. Being a immensely popular monument it is hard to get completely free time with these systems but still we could get very good observation details from the three yantras.

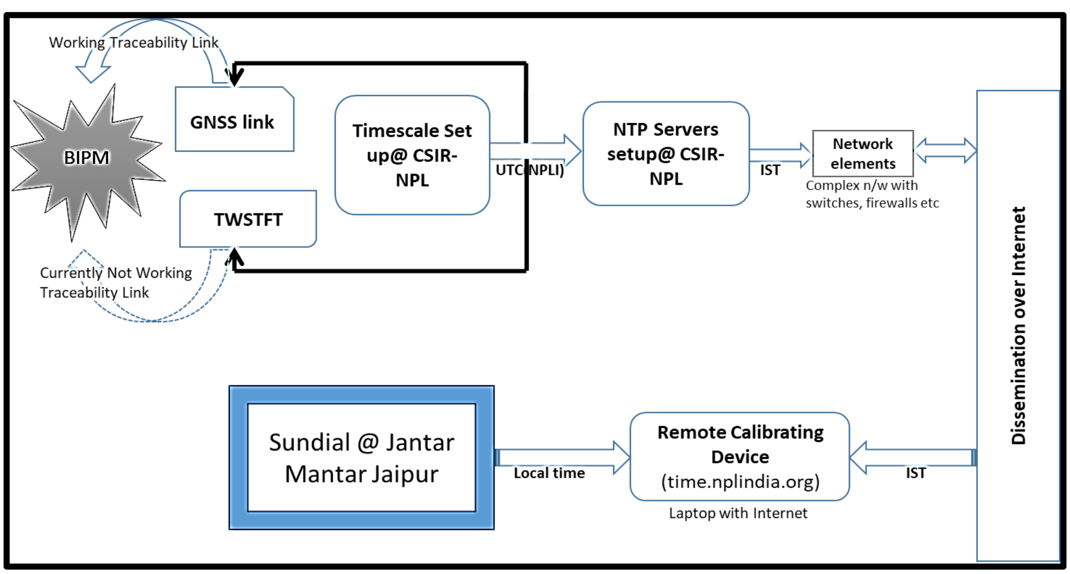

FIGURE 7.10 EXPERIMENTAL SETUP FOR SUNDIAL EVALUATION

7.3.6. Results

Performance of Vrihat Samrat Yantra is as shown in Fig.7.11 and results of performance of Laghu Samrat Yantra are as depicted inFig.7.12.

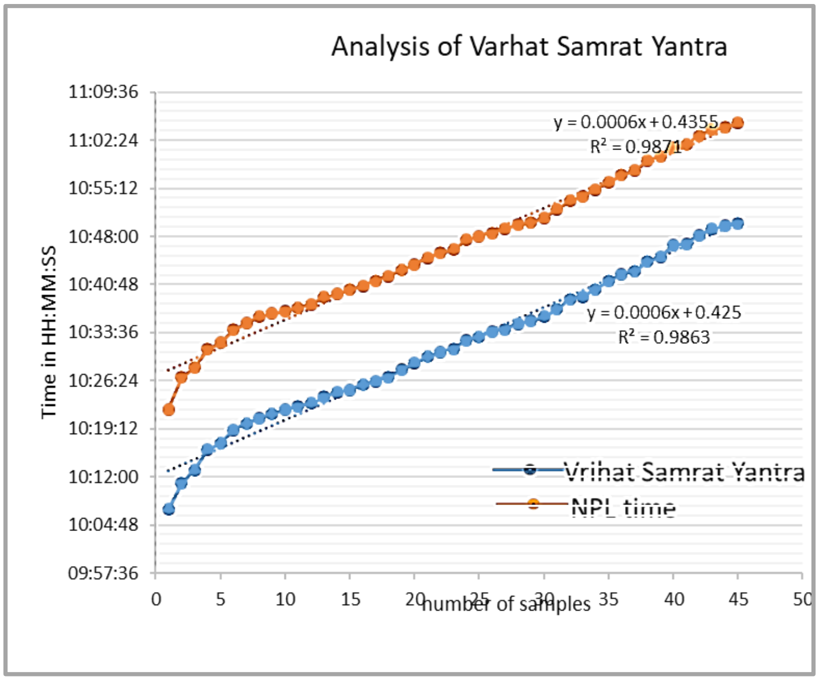

FIGURE 7.11 PERFORMANCE ANALYSIS OF VRAHT SAMRAT YANTRA

And Table 7.2, illustrates offset and jitter values in three yantras.

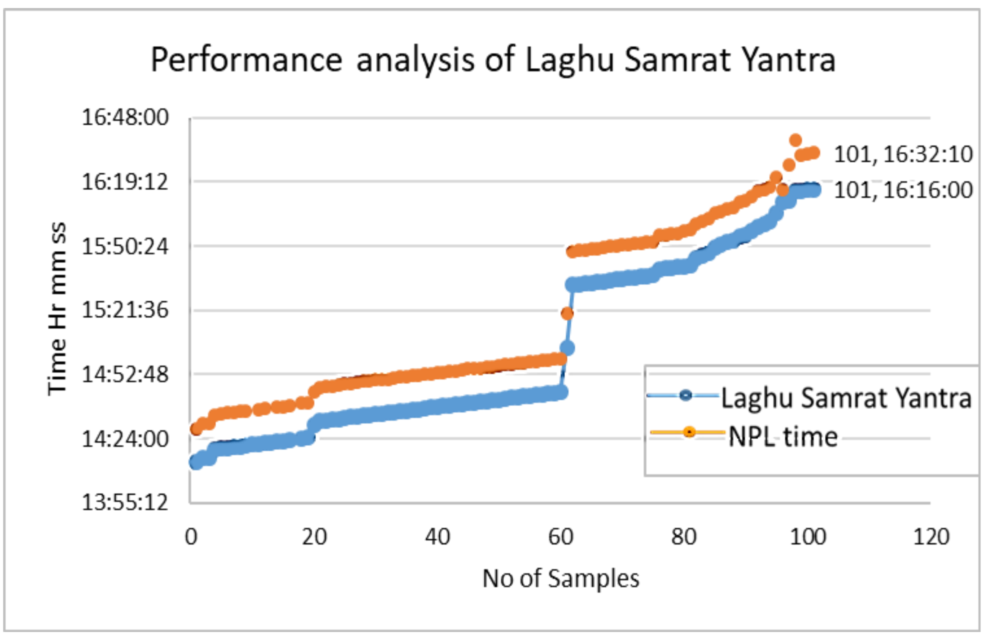

FIGURE 7.12 PERFORMANCE ANALYSIS OF LAGHU SAMRAT YANTRA

TABLE 7.1 COMPUTED OFFSET AND JITTER VALUES IN THREE YANTRAS

Metric	**Nadivalaya Yantra**	**Laghu Samrat Yantra**	**Vrihat Samrat Yantra**
Offset (min)	15.85	15.00	14.93
Jitter (min)	±0.02	±0.53	±0.03

The analysis of sundial performance revealed a systematic offset of approximately 15 minutes, primarily arising from the combined effects of local longitude differences and the equation of time. Despite this offset, the instruments demonstrated notable levels of precision when examined individually. The Nadivalaya and Vrihat Samrat Yantra exhibited highly stable performance with jitter constrained to within ±2 seconds, underscoring their potential as reliable astronomical timekeepers even by modern standards. In contrast, the Laghu Samrat Yantra displayed less stability, with fluctuations reaching up to ±32 seconds, reflecting its limitations in design and scale. The application of digital imaging techniques and computational modeling has enabled finer calibration of these historical instruments, thereby enhancing their alignment with atomic time standards. Beyond technical evaluation, this work emphasizes the broader significance of such efforts: the preservation of cultural and scientific heritage while ensuring traceability to modern timekeeping, thereby creating a meaningful bridge between ancient astronomical practices and contemporary metrology.

7.4. Case Study-2

167 **Analyzing the performance of a Stratum 1 NTP setup established at the National Informatics Centre (NIC).**

7.4.1. Stratum 1 NTP setup at NIC-NKN

The second case study analyses the performance of a Stratum 1 NTP setup established at the National Informatics Centre (NIC), Hyderabad, India [132]

The timescale setup was implemented at the National Informatics Center (NIC), Hyderabad, India, where a Stratum-1 NTP server infrastructure was established. The system was anchored by a Rubidium frequency standard and integrated with a GNSS receiver and an NTP server to ensure the traceability. The same is depicted in fig.7.13.

7.4.2. Methodology

Methodology adopted here is The All-in-View (AIV) GNSS method. This method has proven to be one of the most accurate techniques for remote clock inter-comparison, offering synchronization accuracies on the order of nanoseconds. Unlike the traditional Common View (CV) method, which relies only on satellites visible to both stations simultaneously, the AIV method measures signals from all satellites in view, thereby maximizing data availability, reducing elevation-related errors, and enhancing reliability, especially over large baselines. The experimental set-up for evaluation of timescale performance is as shown in Fig. 7.14.

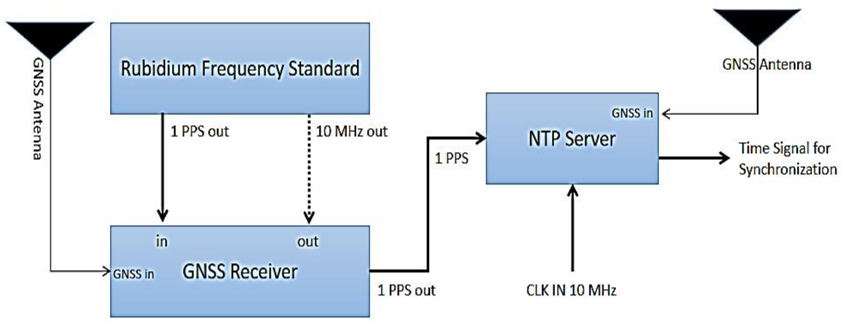

FIGURE 7.13 CLOCK SYNCHRONIZATION SET ESTABLISHED AT NIC-NKN FOR EXPERIMENTAL PURPOSE.

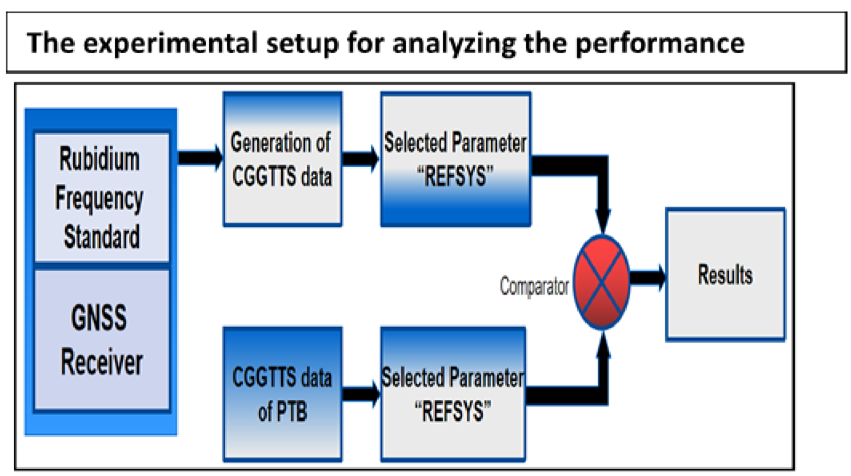

FIGURE 7.14 SET-UP FOR ANALYSING THE PERFORMANCE

The actual installation of the setup is depicted in Fig. 7.15. The antennas of NTP server and GNSS receiver have been installed on 3 side open place having 270 degrees' open to sky access.

FIGURE 7.15 ACTUAL INSTALLATION PICTURES

The receivers, with GNSS server, Rb clock and NTP have been installed in the data center of NIC-NKN, Hyderabad

To assess performance, the time differences between the satellite signals and the ground station were consistently monitored, with comparisons made to the reference kept by the PTB-Germany, using data from the official BIPM database [133]. The analysis adhered to the CGGTTS framework, concentrating on the REFSV parameter, which denotes the offset between the reference user clock and satellite clocks. Time offsets were enhanced through Vondrak smoothing to minimize noise and reveal long-term stability trends. The Rubidium frequency source, exhibiting an uncertainty of around 10^{-10}, served as a reliable reference for assessment. The comparative analysis highlighted the benefits of AIV compared to CV: while CV performance diminishes over extended baselines due to fewer common satellites and lower elevation angles, AIV reliably maximizes satellite utilization, resulting in enhanced accuracy and robustness in time transfer [134].

7.4.3. Results

The comparative analysis of time transfers between PTB (Germany) and NIC Hyderabad (India) reveals clear differences in clock behavior and stability. The PTB trace remains flat and near zero ns, demonstrating excellent long-term stability and accuracy, as expected from a cesium-referenced standard serving as a global anchor in timekeeping. In contrast, the NIC Hyderabad setup, based on a Rubidium (Rb) frequency standard, exhibits a monotonic drift from approximately −1400 ns to 0 ns, followed by a late upward correction. Refer fig. 7.16. This behavior is characteristic of Rb clocks, which typically show smooth short-term stability but suffer from long-term frequency drift due to their inherent uncertainty of about $10^{-10}$when not continuously disciplined by an external reference. Thus, while PTB provides the benchmark stability, the Rb-based system at NIC highlights the practical trade-off between cost-effective local timing and the need for periodic calibration against higher-grade references.

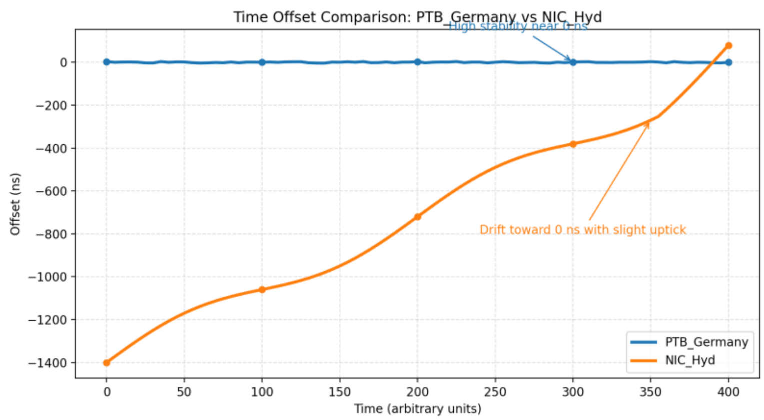

FIGURE 7.16 THE COMPARATIVE ANALYSIS OF TIME TRANSFERS BETWEEN PTB (GERMANY) AND NIC HYDERABAD (INDIA)DEPICTING HE PTB TRACE, REFERENCED TO A CESIUM STANDARD, REMAINS FLAT NEAR 0 NS, DEMONSTRATING EXCELLENT LONG-TERM STABILITY. THE NIC HYDERABAD RUBIDIUM CLOCK SHOWS A MONOTONIC DRIFT FROM APPROXIMATELY −1400 NS TO 0 NS WITH A LATE UPWARD CORRECTION, REFLECTING THE TYPICAL LONG-TERM DRIFT BEHAVIOR OF RB CLOCKS (UNCERTAINTY ~10^{-10}) WHEN NOT CONTINUOUSLY DISCIPLINED.

Evaluating stability metrics as Overlapping Allan deviation was also done. The same is shown in Fig. 7.17and Table 7.4.

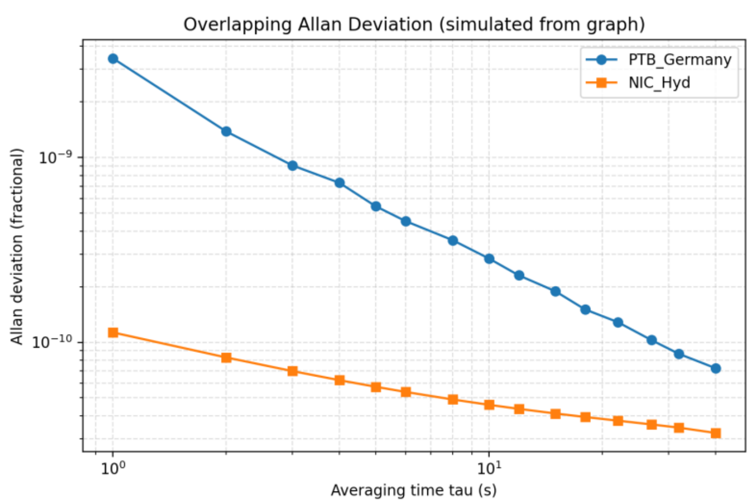

FIGURE 7.17 OVERLAPPING ALLAN DEVIATION COMPARISON BETWEEN PTB (GERMANY) AND NIC HYDERABAD (INDIA). PTB, REFERENCED TO A CESIUM STANDARD, EXHIBITS FRACTIONAL DEVIATIONS IN THE 10^{-9}RANGE, WHILE THE RUBIDIUM-BASED NIC HYDERABAD SETUP ACHIEVES LOWER FRACTIONAL DEVIATIONS NEAR 10^{-10}. THE RESULTS HIGHLIGHT SHORT-TERM STABILITY OF THE RB SYSTEM BUT REFLECT THE SUPERIOR LONG-TERM STABILITY OF THE CESIUM-REFERENCED PTB BENCHMARK

It is clear that, at short averaging times (τ = 1–2 s), the NIC Hyderabad setup shows considerably lower fractional deviations (1.13×10^{-10} and 8.27×10^{-11}) in comparison to PTB (3.43×10^{-9} and 1.38×10^{-9}). This illustrates the established property of Rubidium (Rb) clocks, which provide smoother short-term stability owing to their low phase noise characteristics. The NIC Rb system's superiority in this regime is further highlighted by the Allan deviation plot, where its curve consistently remains below that of PTB during the initial averaging interval.

As the averaging time increases (τ = 10 to 40 s), both systems show enhanced stability, with deviations consistently decreasing. PTB decreases to $7.24{\times}10^{-11}$ at τ = 40 s, whereas NIC Hyderabad reaches $3.23{\times}10^{-11}$, maintaining a slight numerical edge in the short term. Nevertheless, this seeming advantage requires careful interpretation. The PTB system, governed by cesium standards, serves as a reliable anchor for long-term stability, guaranteeing minimal drift over prolonged durations. In contrast, the NIC Hyderabad Rubidium clock, while outstanding in the short term, is recognized for displaying monotonic long-term drift (as indicated by previous offset results), with an uncertainty of around 10^{-10} unless it is continuously disciplined.

TABLE 7.2 NUMERICAL COMPARISON OF ALLAN DEVIATION (ADEV) VALUES FOR PTB GERMANY (CESIUM-REFERENCED) AND NIC HYDERABAD (RUBIDIUM-BASED) ACROSS AVERAGING TIMES (T\TAUT)

T (S)	PTB GERMANY ADEV	NIC_HYD ADEV
1	3.4339×10^{-9}	1.1298×10^{-10}
2	1.3831×10^{-9}	8.2747×10^{-11}
5	5.4383×10^{-10}	5.7399×10^{-11}
10	2.8378×10^{-10}	4.5862×10^{-11}
18	1.5057×10^{-10}	3.9415×10^{-11}
40	7.2440×10^{-11}	3.2311×10^{-11}

Consequently, the combined findings highlight a distinct trade-off: Rubidium clocks demonstrate superior short-term stability, rendering them advantageous for applications that demand consistent and dependable short-term timing, whereas caesium-referenced systems offer unparalleled long-term stability and precision, making them crucial for the establishment of international timescales. The findings highlight the essential and supportive functions of Rb and Cs standards within contemporary timekeeping systems.The outcomes indicate that the configuration is transportable and capable of delivering consistent performance across different deployment sites.

The analysis of historical sundials showed a consistent offset of around 15 minutes due to local longitude and the equation of time. Instruments like the Nadivalaya and Vrihat Samrat Yantra exhibited high precision with jitter within ±2 seconds, while the Laghu Samrat Yantra faced greater instability, up to ±32 seconds. Digital imaging enhanced their calibration, aligning them with atomic standards. And a case study at the National Informatics Centre evaluated a Stratum-1 NTP server using a Rubidium frequency standard, showing superior short-term stability compared to PTB, with fractional deviations of 1.13×10^{-10} *at 1–2 seconds. Conversely, long-term stability favoured the PTB system with caesium standards. These findings underscore the value of integrating traditional instruments with modern timekeeping technologies for metrology and cultural heritage preservation.*

Chapter 8

Conclusions and Future Work

This thesis focuses on enhancing timescale algorithms for national timekeeping systems, aiming to improve accuracy, adaptability, and resilience. Chapter-wise main findings and conclusions presented here.

8.1. Chapter-wise Conclusions

- **Chapter 1: This first chapter introduces the journey**

The introduction provides background information and explains the work's topics and purpose. This chapter illustrates the importance of correct time in science, technology, defence, and communication to demonstrate the importance of the research. It illustrates how accurate timekeeping is essential to progress and work in these disciplines. The chapter explains how timekeeping is crucial to modern systems' growth and reliability by defining it. The research's motivation is obvious, making it easier to investigate. The investigation shows that national timeframe algorithms are not adaptable or strong when challenges arise. This constraint highlights the need for hybrid methods that seamlessly combine conventional filtering methods with advanced AI-driven methods. These two methods can increase timescale algorithm performance and reliability, ensuring they can handle unforeseen changes and remain correct in many settings. Changes in strategy could lead to stronger systems that can manage modern timekeeping concerns.

- **Chapter 2: Literature Review**

This chapter examines our topic's previous study. We will thoroughly study previous studies and theoretical frameworks to strengthen our research. We examine scholarly publications, books, and other resources to identify key themes, gaps, and trends in the subject. The review showed how timekeeping systems have evolved from simple averaging to advanced statistical methods like Kalman filtering. This development highlights how far the field has come and how difficult and accurate modern timekeeping must be. The move from basic to advanced procedures shows how technology and the gr AI and machine learning models like ANN, ARIMA, SVM, and Adaptive Neuro-Fuzzy Inference Systems showed their incredible potential in the study. Advanced approaches can solve atomic clock data problems with non-linear or unusual patterns. These advanced models help researchers understand and enhance timekeeping devices. Many time-measurement-dependent areas will improve greatly. According to the analysis, hybrid approaches that integrate AI and statistical methods are best for developing next-generation time-scales. This strategy combines the finest of AI and statistical analysis, which may yield better results. Combining these strategies may lead to exciting advances as the area changes.

- **Chapter 3: Timescale Algorithm Review**

This chapter compares the algorithms used by key National Metrology Institutes (NMIs) such BIPM ALGOS, NIST AT1, and USNO A.1. The results demonstrate that weighted averaging and Kalman filters are crucial for algorithm stability. Despite these advancements, several issues remain. Noise modelling, real-time adaptation, and anomaly detection are still major issues that must be addressed to improve the algorithm. Pre-processing and hybrid modifications are becoming increasingly necessary. As we study data management and analysis, we see that these tactics are essential to a solid methodology. Combining pre-processing methods cleans raw data and prepares it for analysis. Hybrid innovations allow you to combine methods, improving process efficiency. This underlines the need for a holistic framework that includes pre-processing and hybrid solutions for optimal results.

- **Chapter 4 Data collection details and Methodology**

The study's basic chapter shows how data was obtained systematically to support its goals. The research framework is better understood by emphasising the methodologies. By explaining the methodology, the chapter clarifies how data was acquired, evaluated, and interpreted. This will build the credibility and trustworthiness of the next chapters' findings.This chapter concludes that adequate pre-processing is crucial for dependable atomic clock ensemble data. Setting the groundwork for precise and trustworthy results is crucial. Researcher data quality can be improved by comprehensive pre-processing. This ensures sound analyses and interpretations. The importance of pre-processing in atomic clock research and the need for careful data preparation is shown by this focus. A two-step anomaly filtration system that includes Hampel and Savitzky-Golay has shown remarkable long-term drift control. It removes noise and loud outliers well. This twopronged technique maintains data integrity and preserves crucial trends, making it an effective analytical tool. This approach works well, suggesting it could be valuable in many data-accurate fields. It also fixes several data processing issues. This method cleaned and improved timeframe algorithms' inputs. It enabled efficient filtering and AI integration by providing a solid foundation. To improve algorithms and ensure their performance, input clarity and quality are crucial. Thus, our effort supports present features and enables future technological and approach advancements.

- **Chapter 5: Development of Kalman Filter Timescale Algorithm**

The Kalman filter produced a more stable timescale than simple and weighted averages. The standard deviation was reduced to 1.15 nanoseconds, a substantial improvement over prior approaches' 12 nanoseconds. This large difference indicates how successfully the Kalman filter method produces more consistent and reliable outcomes. It also shows how valuable it could be in demanding accuracy circumstances. The findings suggest that these sophisticated methods may improve data accuracy and reliability. Our extended and 2D Kalman filters have improved system stability and smoothness. By adding dimensions and enhancing algorithms, these filters improve process visualisation. This innovation improves applications and ensures output stability and reliability even with noise and uncertainty. These novel filtering approaches simplify data analysis and interpretation, improving results in various contexts. Kalman filtering is a good starting point for a timeframe, according to the results. This approach is very effective for real-time adaptive correction, demonstrating its reliability. Kalman filtering is ideal for many applications because it generates timescales more accurately and responsively. This strategy ensures precision and flexibility in changing scenarios, which improves performance and results in fast-paced tasks.

- **Chapter 6: Development of Timescale algorithms using AI**

AI and machine learning algorithms improve prediction accuracy. These sophisticated technologies can analyse massive data sets and identify patterns and trends with unprecedented accuracy. Adaptability and response have also increased their resilience. This means these models can work well even when things change or go wrong. The ANFIS model handled data non-linearities and uncertainties well. This technique was important because it could modify and learn from complex patterns. In contrast, the SVM

(RBF) model demonstrated exceptional prediction ability, with a R^2 of 0.9994 and an MSE of 2.44. This accuracy illustrates how well the model predicts, demonstrating how well both approaches solve data problems. Because they were stable, Random Forest approaches outperformed traditional algorithms over time. Random Forest methods are beneficial in many contexts, therefore this dependability is amazing. They operate better than traditional treatments and maintain results over time, which is crucial. Random Forest approaches can be used. The investigation shows that AI-improved timeframes are more accurate, adaptable, and robust than traditional techniques. AI can improve many processes, making results more precise and adaptive. Knowing more about AI makes it evident that longer timescales impact how we solve problems and make decisions in many areas. This has major implications, showing that AI-driven solutions will be the standard for optimal results.

- **Chapter 7: Application of efficient timescale in National Timescale Dissemination**

Two case studies provide important information about using the framework in practice. The first case study illustrates how to calibrate the Jaipur Jantar Mantar sundial remotely using traditional astronomy equipment combined with contemporary technologies. The second case study describes how the National Informatics Centre in Hyderabad improved modern time synchronisation with Stratum-1 NTP. These examples demonstrate that the framework can integrate traditional methods with new technologies, confirming its relevance. All-in-View GNSS methods demonstrated nanosecond accuracy, showing their precision and reliability for many applications. Systems that require accurate time and location information need this accuracy. Currently, NTP time dissemination works successfully on many digital infrastructures. Time synchronisation is stable and consistent, which is crucial for networked systems. These technologies demonstrate how timing solutions have enhanced various fields. The results showed that the system works for national and dispersed time sharing. This shows that the method works and handles time distribution issues well. To make sure the framework works in many scenarios, we extensively examined its operational elements. Overall, the results indicate that the framework will improve national and distributed time dissemination practices.

This dissertation has effectively developed an efficient timescale algorithm, addressing the essential criteria of accuracy, adaptability, and resilience in national timekeeping systems. It has successfully addressed all four objectives covering analysis of various Timescale algorithms, evaluation of various pre-processing techniques, development of a pre-processing algorithm, development of a Kalman filter-based Timescale algorithm and Application of AI Techniques and application of the Timescale in the dissemination of national timescale.

8.2. Future Scope

While the proposed framework has demonstrated significant advances, the following directions remain open for further exploration and development:

8.2.1. Hardware Deployment

Transitioning from software simulations to real-time hardware platforms such as FPGAs, embedded processors, or ASICs would enable low-latency, energy-efficient implementations. Such systems would be critical for mission-critical applications**,** including defence, satellite navigation, and real-time financial transactions.

8.2.2. AI-Driven Fault Diagnostics and Autonomous Operation:

Future work could expand the role of AI models toward fully autonomous timescale management, enabling self-correcting, fault-tolerant frameworks that dynamically adapt to anomalies or hardware failures without manual intervention.

8.3. Closing Remarks

This work emphasises the revolutionary capacity of AI-enhanced timescale algorithms in reshaping the future of timekeeping. This dissertation creates a framework that not only makes the country more resilient but also helps with the global synchronisation that is
12 necessary for science, technology, and society. It does this by combining the rigour of traditional statistical methods with the flexibility of modern machine learning.

List of Publications

Journal Publications

1. **Pranalee P Thorat**, Ravinder Agarwal and D. K Aswal, "Kalganana: India's Participation Towards Timescale from Ancient Time to the Current Date: Nimesha to Universal Coordinated Time (UTC)", MAPAN- Journal of Metrology Society of India, Vol. 38, pp 44-7, 2022
2. **Pranalee P Thorat**, Ravinder Agarwal, Venu Gopal Achanta, "Remote Calibration of Sundials of Jantar Mantar Jaipur Rajasthan and its Traceability with IST", MAPAN- Journal of Metrology Society of India, Volume 40, pages 459–469, 2025
3. G Kumar, **Pranalee P Thorat**, Ravinder Agarwal and D. K Aswal, "A study of Internet Time Dissemination Services and their Capabilities: NTP as a Special case in Time Metrology", MAPAN- Journal of Metrology Society of India, Vol. 37, pp 421-434, 2022
4. **Pranalee P. Thorat***et al*, "Novel Approach to Synchronize National Knowledge Network (NKN) of National Informatics Centre (NIC) Network with IST over IoT Framework", International Journal of Engineering and Advanced Technology, Vol 4, pp 44-52, 2023

Book Chapter

Pranalee P Thorat, Ravinder Agarwal, D. K. Aswal, "Precise Time Transfer Techniques – Part I: Telephone, LWR and Network", In book: Handbook of Metrology and Applications (pp.1-53) April 2023, DOI:10.1007/978-981-19-1550-5_22-1

Papers presented in National and International Conferences

1. **P. P. Thorat**, R. Agarwal, and V. G. Achanta, "Enhancement of precision clock stability and timekeeping accuracy of UTC(NPLI) through Kalman filter integration," in *Proc. AP-RASC 2025 – URSI Asia-Pacific Radio Science Conference*, Sydney, Australia, Aug. 17–22, 2025.
2. **P. P. Thorat**, R. Agarwal, and V. G. Achanta, "Role of AI in calibrating instruments for precise and accurate radio astronomy," in *Proc. AP-RASC 2025 – URSI Asia-Pacific Radio Science Conference*, Sydney, Australia, Aug. 17–22, 2025.
3. **P. P. Thorat**, R. Agarwal, and V. G. Achanta, "An ANN-based Prediction Model to Predict the Time Offset between the On-Board Satellite Clock and Reference Clock at Ground Station," in *Proc. 3rd Int. Conf. Intelligent Computing, Instrumentation and Control Technologies (ICICICT 2022)*, Mar. 4, 2022
4. **P. P. Thorat**, G. Kumar, R. Agarwal, and V. G. Achanta, "Application of GA technique to optimize the performance of NTP server," in *Proc. 6th Int. Conf. Computing, Communication, Control and Automation (ICCUBEA-2022)*, Pune, India, 2022. IEEE.

5. **P. P. Thorat,** G. Kumar, R. Agarwal, and V. G. Achanta, "Analyzing the effects of cyber threats on NTP IST dissemination service and measures for their effective mitigation," in *Proc. 6th Int. Conf. Computing, Communication, Control and Automation (ICCUBEA-2022)*, Pune, India, Aug. 2022. IEEE.
6. **P. P. Thorat**, G. Kumar, R. Agarwal, and V. G. Achanta, "An ANN-based prediction model to predict the time offset between the on-board satellite clock and reference clock at ground station," in *Proc. Int. Conf. Intelligent Computing, Instrumentation and Control Technologies (ICICICT-2022)*, Kerala, India, 2022. IEEE.
7. **P. P. Thorat**, G. Kumar, R. Agarwal, and V. G. Achanta, "NTP server traffic prediction model using artificial neural network," in *Proc. Int. Conf. Intelligent Computing, Instrumentation and Control Technologies (ICICICT-2022)*, Kerala, India, 2022. IEEE.
8. **P. P. Thorat**, G. Kumar, R. Agarwal, and V. G. Achanta, "Analyzing the performance of Stratum-1 NTP setup established at NIC, Hyderabad, India," in *Proc. 11th Int. Conf. Advances in Metrology (AdMet-2022)*, CSIR-NPL, New Delhi, India, 2022.
9. **P. P. Thorat**, G. Kumar, R. Agarwal, and V. G. Achanta, "Performance evaluation of Stratum-1 NTP server with IRNSS and GPS using the TeLit EVK card," in *Proc. 11th Int. Conf. Advances in Metrology (AdMet-2022)*, CSIR-NPL, New Delhi, India, 2022.
10. **P. P. Thorat** and P. Banerjee, "A study on the impact of Kalman filtering on CGTTS formatted GPS data for time transfer," in *Proc. URSI Regional Conf. Radio Science (URSI-RCRS 2022)*, IIT Indore, India, Dec. 1–4, 2022. doi: 10.23919/URSI-RCRS56822.2022.10118486.
11. **P. P. Thorat**, G. Kumar, R. Agarwal, and V. G. Achanta, "AI-ANN based prediction model: Prediction of client-server time offset of NTP service of CSIR-NPL," in *Proc. URSI Regional Conf. Radio Science (URSI-RCRS 2022)*, IIT Indore, India, Dec. 1–4, 2022.
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14. **P. P. Thorat**, G. Sharma, R. Agarwal, and D. K. Aswal, "TeraHertz (THz) Wireless Communication for Satisfying the Demand of Higher Data Rates with Greater Security," in *Proc. Int. Conf. Frontier of Terahertz Technology & Applications (FTTA 2021)*, Dec. 9–11, 2021

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