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SCSO-MHEF: Sand Cat Swarm Optimization based MHEF for Nonlinear LTI-IoT Sensor Data Enhancement

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ABSTRACT- Sensor data is an integral component of internet of things (IoT) and edge computing environments and initiatives. In IoT, almost any entity imaginable can be outfitted with a unique identifier and the capacity to transfer data over a network. The estimate problem was formulated as a min-max problem subject to system dynamics and limitations on states and disturbances within the moving horizon strategy framework. In this paper, a novel Sand Cat Swarm Optimization Based MHEF for Nonlinear LTI IOT Sensor Data Enhancement (SCSO-MHEF) is proposed. In the proposed method the MHEF is optimized using Sand Cat Swarm Optimization to enhance sensor data stability tuned by initial parameters. Simulation experiments were conducted on various and unique scenarios in various orders LTI system with IOT sensor data in order to validate the suggested approach. This method can be used to analyze systems with dynamically changing systems. The proposed SCSO-MHEF technique overall accuracy of 84.5%, 87.3 %, and 99.5 % better than Kalman Filter (KF), EKF and Moving Horizon Filter (MHEF) respectively.

Keywords: Moving Horizon Estimation, Internet of Things, Kalman Filter, Extended Kalman Filter.

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1. INTRODUCTION

Internet of Things describes a broad network of interconnected objects as well as the technologies that enable communication between devices and the cloud, as well as between them [1, 2]. Enhancing the quality and accuracy of data obtained from IoT devices is known as IOT sensor data improvement [3]. This can involve techniques such as data cleaning, normalization, and filtering, as well as leveraging machine learning algorithms to identify patterns and anomalies in the data [4,5]. The goal of sensor data enhancement is to ensure that the data collected from IoT devices is reliable, accurate, and actionable, which can help organizations make better decisions and improve their operations [6,7].

Moving horizon estimating (MHE) is an optimization technique that yields estimates of unknown variables or parameters by utilizing a sequence of measurements taken over time that may contain noise (random changes) and other errors [8,9]. In contrast to deterministic methods, MHE necessitates an iterative strategy that uses solvers for either linear or nonlinear programming to find a solution [10]. Under some simplifying assumptions, MHE reduces to the Kalman filter. An analysis comparing the MHE to the extended Kalman filter revealed that while the MHE reduced computing costs, it boosted performance. [11] MHE has often been used in systems with moderate to sluggish system dynamics and more computer resources because to its high computational cost. Nonetheless, there are various techniques in the literature to quicken this method [12].

Nonlinear LTI-IoT sensor data enhancement refers to the use of linear time-invariant (LTI) algorithms to improve the quality and accuracy of sensor data collected from the internet of things (IoT). These algorithms can remove noise, filter out unwanted signals, and enhance the overall performance of the sensor data [13,14]. By applying nonlinear LTI techniques to IoT sensor data, you can gain a deeper understanding of the data and make more informed decisions [15]. Problem To overcome this issue a novel Sand Cat Swarm Optimization based MHEF for nonlinear LTI-IoT sensor data enhancement (SCSO-MHEF). The major contribution of the work has been followed by,

- In the proposed method the MHEF is optimized using Sand Cat Swarm Optimization to enhance sensor data stability tunned by initial parameters.
- Simulation experiments were conducted on various and unique scenarios in various orders LTI system with IOT sensor data in order to validate the suggested approach.
- SCSO-MHEF method can be used to analyze systems with dynamically changing systems.
- The proposed SCSO-MHEF technique overall accuracy of better than Kalman Filter (KF), EKF and Moving Horizon Filter (MHEF) respectively.

The remaining portion of the work has been followed by *Section 2* illustrate the literature survey, *Section 3* illustrate the proposed SCSO-MHEF, *Section 4* illustrate the Result and Discussion and *Section 5* illustrate the conclusion of the proposed SCSO-MHEF technique.

2. LITERATURE REVIEW

The discrete-time situation and the continuous-time case have each been studied in [16-18] in turn. The set-valued estimating technique seeks to construct ellipsoids around state estimations that are both consistent with the observations and subject to particular norm constraints with regard to the noise disturbances [19]. For all permitted model uncertainties, the steady-state variance of the state estimate error is upper limited by a given constant value, thanks to the careful design of the filters utilized in the guaranteed cost technique [20]. Requirements regarding date uncertainty must be satisfied in order to minimize the worst-case residual energy at each iteration [21]. In actuality, though, inequality restrictions provide additional information about the process. However, broad estimation techniques like the robust filtering algorithm and Kalman filtering, which were previously available, are no longer available with the addition of inequality restrictions.

Moving horizon estimate (MHE), which builds on the success of receding horizon control, has been proposed as a workable method to include inequality constraints in estimating [22]. A moving fixed-size estimate window and a quadratic programme are used to design the estimation issue as part of the fundamental MHE technique [23]. Recently, MHE has attracted a lot of interest and has shown to be an effective method for estimating the state of restricted systems. Unconstrained linear MHE stability with smoothing and filtering updates [24]. MHE is a practical strategy for limited state estimation, as demonstrated by moving horizon techniques for constrained linear state estimates [25]. We developed the resilient moving horizon estimation (RMHE) approach for the restricted linear system with an unknown model, as opposed to the MHE and robust filter discussed above.

Although, several advancements are made in Nonlinear LTI, IOT faces a number of Challenges identified are lack of ontological knowledge of what counts as Nonlinear LTI, how it is assessed and its validity and integrity. The data reveal high demands regarding training on issues of assessment and raising awareness of Nonlinear LTI at the institution. To overcome this issue a novel Sand Cat Swarm Optimization Based MHEF for Nonlinear LTI-IOT Sensor Data Enhancement (SCSO-MHEF) is proposed.

3. PROPOSED METHODOLOGY

In this section, a novel Sand Cat Swarm Optimization Based MHEF for Nonlinear LTI-IOT Sensor Data Enhancement (SCSO-MHEF) is proposed. In the proposed method the MHEF is optimized using Sand Cat Swarm Optimization to enhance sensor data stability tunned by initial parameters. Proposed SCSO-MHE FILTER Implementation is shown in *figure.1*

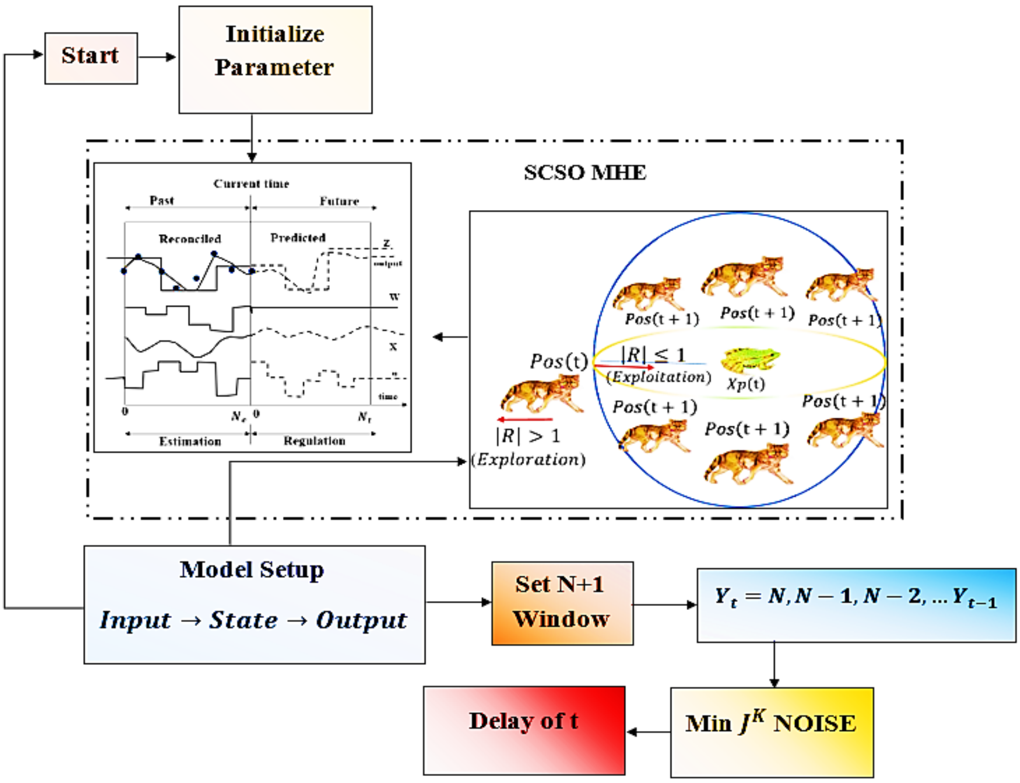

Figure 1. Proposed SCSO-MHE FILTER Implementation

3.1 Transient response analysis of hybrid LFC system tuned with BWO algorithm

Moving horizon estimate use a sliding temporal frame. Every sampling interval, the window advances by one step. By examining the observed output sequence, it guesses the states within the window and utilizes the most recent estimated state outside of the window as previous knowledge.

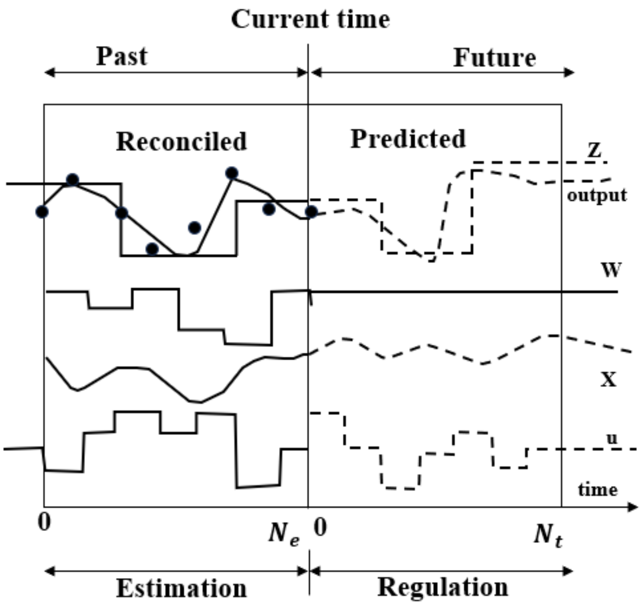

Figure 2. Moving Horizon Estimation

The estimate and regulatory horizons are established in *figure 2*. In real-world applications, they are frequently chosen adaptively such that the answers to the mathematical programs with finite sizes roughly correspond to the answers to the equivalent full-horizon issues. Just as a cost to go function is used to roughly account for the future beyond the regulator window, so too is the information in the past data outside the estimate window approximated by a cost to arrive function rather than eliminated. This suggests that even while the moving horizon approximation limits and reduces the sizes of the mathematical programs that make up the regulator and the estimator, such programs may still be substantial in size.

$$\min_{\{A_i,B_j\}_{i=k-m}^{k-1}} \sum_{i=k-M}^{k=1} ||V_i||^2_{P^{-1}} + \sum_{i=k-M+1}^{k} ||U_i||^2_{R^{-1}} + \varphi_{k-M} \quad (1)$$

The current time interval is represented by k, the length of the horizon is denoted by *M*, the process uncertainty, measurement noise, and states are represented by the covariance matrices P and R, respectively, and the vectors *V*, *U*, *A*, and *B* describe the system's states, inputs, outputs, and measurement noise, respectively.

$$\varphi_{k-M} = ||A_{k-M} - \bar{A}_{k-M}||^2_{Q^{-1}_{k-M}} \quad (2)$$

Where, $\bar{A}_{k-M}$ and Q_{k-M} represent the expected value and covariance matrix of the estimated posterior distribution of the states at time interval k M, respectively.

3.2 Sand Cat Swarm Optimization

The Sand Cat Swarm Optimization (SCSO) algorithm is a novel SI-based metaheuristic. Based on the desert cats' particular hearing and hunting abilities, this system can respond fast and undertake exploration-exploitation processes in a balanced manner.

The sand cat swarm optimization (SCSO) technique is based on natural sand cat activities. The SCSO algorithm simulates this animal's search and hunting function. The sand cat differs from domestic cats in several ways, including its capacity to hear low frequency noises, its ability to thrive in the harsh environment of deserts, and its own hunting techniques. Both cat kinds have the same look, however the sand cat has more fur in the palms and soles. As previously stated, the sand cat has a unique technique of foraging and hunting. They forecast the position of the prey based on their exceptional capacity to hear low-frequency sounds.

$$\vec{e}_s = C_N - \left(\frac{C_N * iter_l}{iter_{max}}\right) \quad (3)$$

Where, C_N which is associated with the sand-cat's ability to catch low-frequencies below 2 KHz, is assumed to be 2, $iter_l$ is the current iteration number, and $iter_{max}$ is the iterations maximum value.

$$E = 2 * \vec{e}_s * eand(0,1) - \vec{e}_s \quad (4)$$

$$\vec{e} = \vec{e}_s * eand\ (0,1) \quad (5)$$

The SCSO algorithm empowers the hunting for food by utilizing each sand cat's capacity to emit low-frequency noise. Each search agent's sensitivity range (*E*) is preset between 2 and 0. The $\vec{e}_s$ parameter indicates the general sensitivity range which decreases from 2 to 0 according to *eq. 4 and 5*

$$\vec{A}\ (t+1) = \vec{e}.\left(\vec{A}_{y(t)} - eand\ (0,1).\vec{A}_{d(t)}\right) \quad (6)$$

$$\vec{A}_{end} = |eand\ (0,1).\vec{A}_{y(t)} - \vec{A}_{d(t)}| \quad (7)$$

$$\vec{A}(t+1) = \vec{A}_{y(t)} - \vec{e}.\vec{A}_{rnd}.\cos\alpha \quad (8)$$

Where, $\vec{A}_l$ indicates the current position, $\vec{A}_y$, and $\vec{A}_{end}$ is the random position according to eq 6,7 and 8.

$$\vec{A}(t+1) = \begin{cases} \vec{e}.\left(\vec{A}_{y(t)} - eand\ (0,1).\vec{A}_{d(t)}\right) & |R| > 1 \\ \vec{A}_{y(t)} - \vec{e}.\vec{A}_{rnd}.\cos\alpha & |R| \le 1 \end{cases} \quad (9)$$

Every search agent in the SCSO algorithm travels on a circular path, searching for potential global solutions by moving in various directions. The random angle α, which ranges from 0 to 360, is regarded as a $\cos(\alpha)$ function. *Equation (9)*, for the SCSO method, provides the primary structural equations.

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3.3 SCSO-MHE Filter for IoT Sensor Data

3.3.1 Sensing layer

Data coming from various IoT devices is gathered using this layer. The lowest layer that was seen in the suggested framework is this one. It records the different heterogeneous types of data obtained from heterogeneous Internet of Things devices, such as sensors, actuators, protocols, and data formats, etc. The significant volume of big data is passed on to the following layer. Raw data processing and data analysis are done at the data processing layer. Proposed framework for IoT sensor data is shown in *figure 3*.

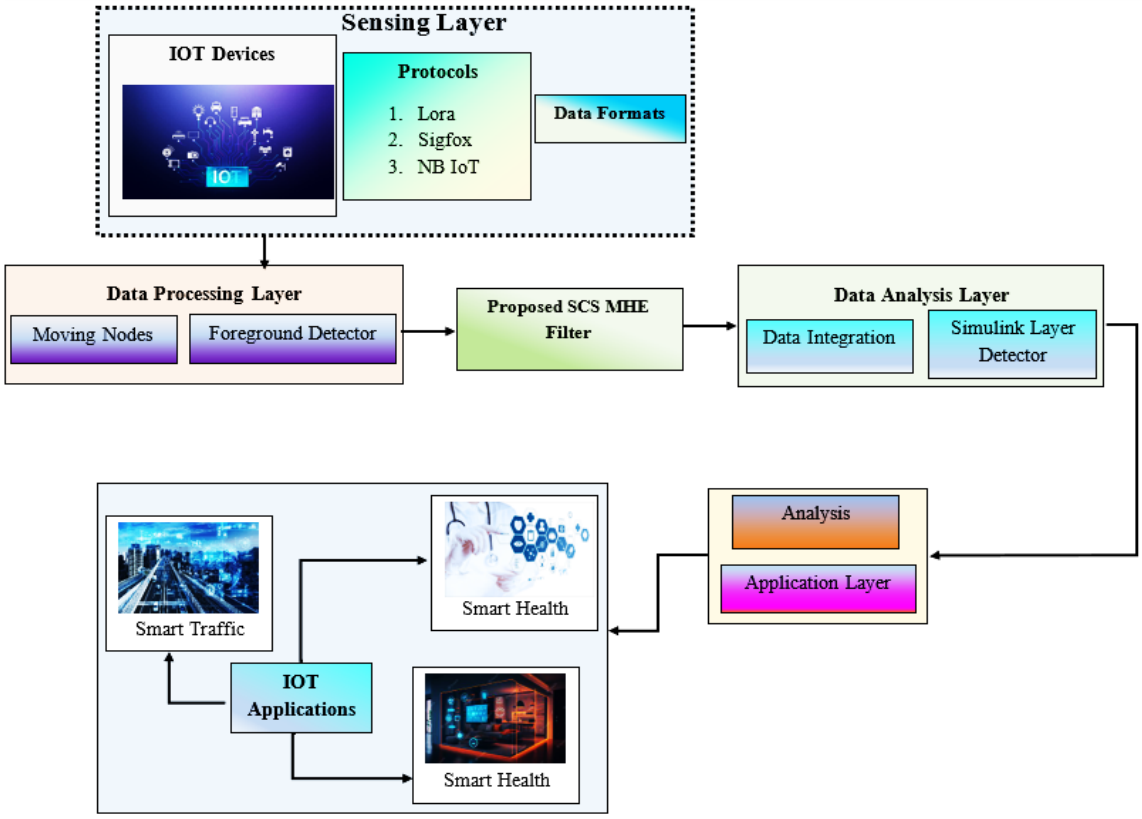

Figure 3. Proposed framework for IoT sensor data

3.3.2. Data processing layer

This layer is used to extract the necessary information from the physically obtained raw data. The two sub-modules of the feature extraction and foreground detector data make up the majority of the data processing layer.

3.3.3. Data analysis layer

For the suggested framework, this is the most important layer. This layer has the Simulink model applied to it. To annotate the IoT sensor data, the data will be taken after pre-processing has been conducted on the data processing layer.

3.3.4. Application layer

As part of the Thing Speak cloud platform, this layer is utilized to analyze and present the users' IoT sensor data that has been acquired. In real-time settings, this layer generates traffic alerts and vehicle counts.

4. RESULTS AND DISCUSSION

This section evaluates and analyses the suggested SCSO-MHEF method's performance. The suggested technique is implemented using MATLAB2020b running on a Windows 10 OS with an Intel i3 core processor at 2.10 GHz and 8GB RAM. MHE's predictive nature allows it to take into account multiple measurements over a limited time period, producing predictions that are more precise, especially when anomalies and disturbances are present. Due to their reliance on linearization assumptions and limited consideration of prior observations, traditional estimators may exhibit lower accuracy in dynamic and unpredictable contexts.

Table 1. Comparison of performance evaluation of MHS with Linear system

Filter	Accuracy	Efficiency	Complexity
EKF	83.3%	68.07	Low
Kalman Filter (KF)	80%	69.82	Low
Moving Horizon Filter (MHF)	91%	72.56	High

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It is widely used to evaluate the accuracy of a regression model. MSE is significant because it calculates the usual error between measured values that are actually taken and those that are projected. The *table 1* demonstrates that the model mentioned above provides a useful method for reducing MSE values in linear systems. In contrast, the system appears to be effective.

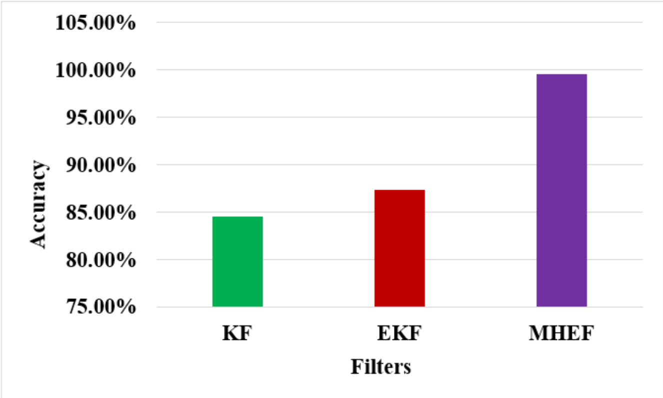

Figure 4. Comparison based on Filters

The proposed SCSO-MHEF technique overall accuracy of 84.5%, 87.3 %, and 99.5 % better than Kalman Filter (KF), EKF and Moving Horizon Filter (MHEF) respectively. Comparison based on Filters is shown in *figure 4*.

Table 2. Comparison of performance evaluation of MHS with Non-Linear system

Filter	Accuracy	Efficiency	Complexity
Kalman Filter (KF)	84.5%	78.92	Moderate
EKF	87.3%	82.07	Moderate
Moving Horizon Filter (MHEF)	99.5%	85.75	Moderate

In comparison to the nonlinear MHF mechanism, the suggested model gives improved accuracy, as shown in *table 2*, the capacity of a system or process to continue to function steadily under difficult or unexpected circumstances. In contrast, the system appears to be more durable.

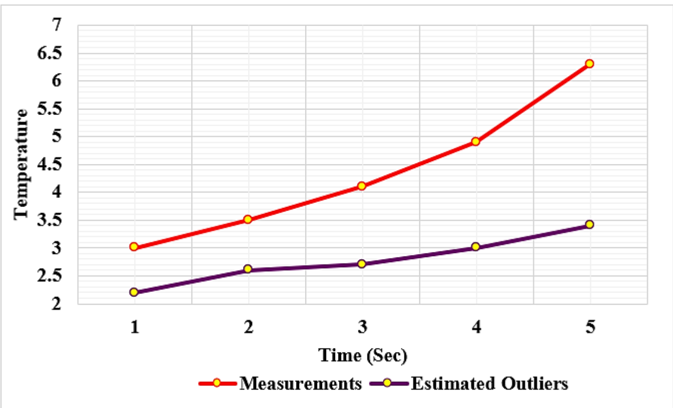

Figure 5. MHE -based nonlinear temperature estimation

The moving horizon technique uses an optimization algorithm to decide what control action to take at each time step. In the graph of *figure 5* shows nonlinear systems using temperature estimation the moving horizon approach, the effectiveness of the control strategy in regulating the output of a linear dynamic system is displayed. It is possible to analyses the graph to determine the details of the strategy depicted in *figure 6*, including its capability to track set points, robustness to shocks, and control effort.

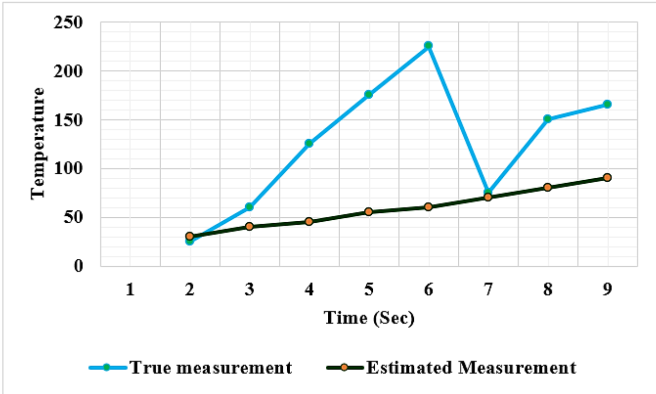

Figure 6. Nonlinear temperature estimation

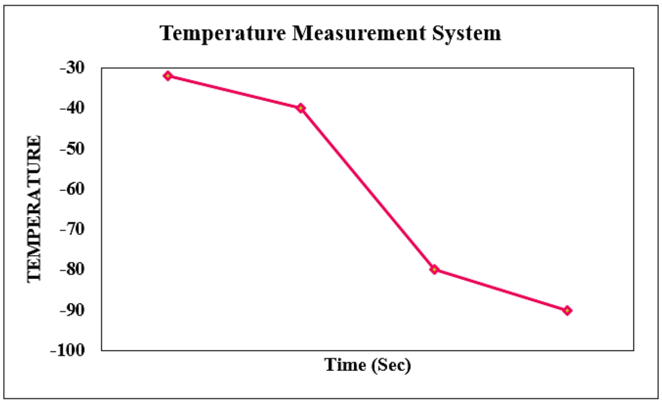

Figure 7. MHE-based linear temperature estimation

In *figure 7*, the time updates are computed to forecast the system's future state, and the measurement updates are computed to modify the state estimation in light of the most recent measurement.

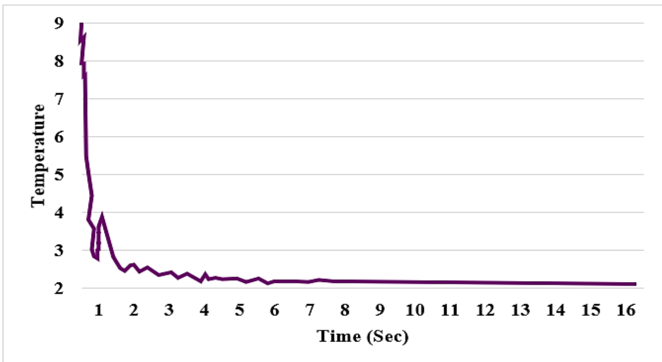

Figure 8. Estimation of linear temperature

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Figure 8 displays the output signal both with and without outliers, and uses a MHEF to estimate the system state from the output signal while also displaying linear temperature estimation. The output is compared to the original output signal to see how well the filter worked.

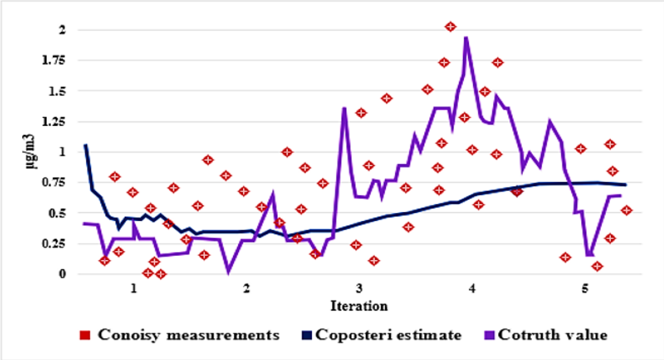

Figure 9. Iterative convergence process

The repeated convergence procedure at Q = 0 is seen in *figure 9*. In the graphic, the green line represents the data from the monitoring site, which indicates the real value, the blue line represents the output of the MHEF in each iteration, and the plus sign represents the observed value with mistakes by the sensors.

4.1 Discussion

In the proposed method the MHEF is optimized using Sand Cat Swarm Optimization to enhance sensor data stability tunned by initial parameters for data enhancement. The result section evaluates and analyses the suggested SCSO-MHEF method's performance. The *table 1* demonstrates that the model mentioned above provides a useful method for reducing MSE values in linear systems. In contrast, the system appears to be effective. The proposed SCSO-MHEF technique overall accuracy of 84.5%, 87.3 %, and 99.5 % better than Kalman Filter (KF), EKF and Moving Horizon Filter (MHEF) respectively. Comparison based on Filters is shown in *figure 4. figure 5*. Represents the MHE -based nonlinear temperature estimation, *figure 6*. Represents the MHE -based nonlinear temperature estimation, *figure 7*. Represents the Nonlinear temperature estimation. As a result, the proposed SCSO-MHEF technique has been found to be unique, with better accuracy.

5. CONCLUSION

In this section, a novel Sand Cat Swarm Optimization Based MHEF for Nonlinear LTI IOT Sensor Data Enhancement (SCSO-MHEF) is proposed. In the proposed method the MHEF is optimized using Sand Cat Swarm Optimization to enhance sensor data stability tunned by initial parameters. Simulation experiments were conducted on various and unique scenarios in various orders LTI system with IOT sensor data in order to validate the suggested approach. This method can be used to analyze systems with dynamically changing systems. The proposed SCSO-MHEF technique overall accuracy of 84.5%, 87.3 %, and 99.5 % better than Kalman Filter (KF), EKF and Moving Horizon Filter (MHEF) respectively. The advantages of the proposed over existing technique is that the proposed SCSO-MHEF method attains high accuracy of the estimated state of a system based on nonlinear LIT, time-varying, or noisy sensor measurements. Future studies might focus on applying this technique to improve performance in other fields. Focusing on enhancing and expanding the suggested method to estimation for higher order nonlinear systems and in the presence of many anomalies can advance the research in the future.

Author Contributions: The authors confirm contribution to the paper as follows: study conception and design: Anees Fathima Bashir, M. P. Flower Queen; data collection: Irfan Habib; analysis and interpretation of results: Anees Fathima Bashir; draft manuscript preparation: M. P. Flower Queen All authors reviewed the results and approved the final version of the manuscript.

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Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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