

RESPONSE FILE

We would like to thank the anonymous reviewer for his/her careful reading of our manuscript and for coming up with several insightful comments and suggestions. As per the given suggestions, the authors have addressed all the concerns.

Reviewer(s)' Comments to the Author

Reviewer #3:

1. “However, the existing detection methods for electric vehicle insulation resistance, including comprehensive detection and fault location, are inadequate for meeting the growing demands for electric vehicle insulation detection.” Please explain in detail why the existing electric vehicle insulation resistance testing methods, including comprehensive detection and fault location, are insufficient to meet the growing demand for electric vehicle insulation testing.

Response: The authors are thankful to the reviewer for their valuable suggestions. The demand for electrical vehicles is gradually increasing, so the features in vehicles and different types of vehicles are also increasing. The electrical faults are also increasing, and the electrical faults mainly occur due to insulation degradation and loss of strength of insulation. There are many methods, like offline (voltmeter method, megohmmeter measurement method), online (balanced and unbalanced bridge methods, low-frequency signal and high-frequency signal injection methods), for the detection of the insulation. Among all these methods, the speed of detection is very important. The speed can be improved by using an FPGA-based method for the detection of the insulations.

2. “Voltmeter measurements are only accessible offline.” Please elaborate on why voltmeter measurements are only accessible offline.

Response: Authors are thankful to the reviewer for their valuable suggestion. In order to determine the insulation resistance of the positive and negative poles of the high-voltage direct-current (HVDC) system with regard to the automotive electrical chassis, a high-precision voltmeter is typically used to measure the voltage of the HVDC system supplied to the electrical chassis. This technique does not assess the insulating resistance of the HVDC system under real driving conditions since it needs an electric vehicle to be stopped for static testing. As a result, the benefits of promoting electric vehicles are lost.

3. “We examined the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) [26] to estimate the insulation resistance using the voltage injection model. This approach enhances the

precision of the detection outcomes.” Please explain in detail why Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) improve the accuracy of detection results.

Response: Authors are thankful to the reviewer for their valuable suggestion.

Explanation:

The Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF) are both variants of the Kalman filter, which is a recursive algorithm for estimating the state of a dynamic system from a series of noisy measurements. In the context of above statement about estimating insulation resistance using the voltage injection model, let's discuss how EKF and UKF enhance the precision of detection outcomes.

-Nonlinear System Models:

The voltage injection model for estimating insulation resistance is often nonlinear. Traditional Kalman filters are designed for linear systems, and using them directly on nonlinear models can lead to suboptimal performance. EKF and UKF are specifically designed to handle nonlinear systems. They linearize the system model at each iteration (for EKF) or use a set of carefully chosen points (sigma points) to capture the system's nonlinear behaviour (for UKF).

-Linearization in EKF:

EKF linearizes the system dynamics and measurement equations at each time step. It essentially replaces the nonlinear equations with linear approximations by computing the Jacobian matrices. This allows EKF to provide more accurate estimates in the presence of nonlinearities compared to a standard Kalman filter.

-Sigma Points in UKF:

UKF, on the other hand, avoids explicit linearization. Instead, it uses a set of sigma points that capture the distribution of the state variables. These sigma points are transformed through the nonlinear functions of the system model. By using these sigma points, UKF captures the nonlinearities more accurately than EKF and traditional Kalman filters, making it particularly effective for systems with strong nonlinearities.

-Better Handling of Non-Gaussian Uncertainties:

Both EKF and UKF are better equipped to handle non-Gaussian uncertainties compared to linear Kalman filters. Nonlinear systems often lead to non-Gaussian state distributions, and EKF and UKF are designed to propagate and update the mean and covariance of these distributions more accurately.

-Robustness to Model Errors:

EKF and UKF are generally more robust to errors in the system model. If there are inaccuracies or uncertainties in the model used for estimating insulation resistance, these filters can still provide reasonable estimates by adapting to the actual system behaviour.

-Adaptability and Stability:

EKF and UKF adapt to the changing dynamics of the system over time, making them more suitable for situations where the system characteristics may vary. UKF, in particular, is known for providing stable estimates even in cases of highly nonlinear and non-Gaussian systems.

In conclusion, the precision improvement in detection outcomes when using EKF and UKF for estimating insulation resistance in the voltage injection model is mainly due to their ability to handle nonlinearities more effectively, adapt to changing system conditions, and provide accurate estimates in the presence of uncertainties and model errors. These features make them powerful tools for state estimation in dynamic systems with nonlinear characteristics."

4. “This is advantageous for adaptive filter algorithms because it enables parallel computing of filter coefficients, resulting in faster processing times.” Please explain in detail why the adaptive filter algorithm can calculate filter coefficients in parallel, thereby reducing processing time.

Response: Authors are grateful to the reviewer for bringing out this point into their consideration.

Explanation:

The statement suggests that parallel computing of filter coefficients is advantageous for adaptive filter algorithms, leading to faster processing times. Let's break down the reasons behind this advantage:

-Independence of Coefficient Updates:

In an adaptive filter, the filter coefficients are updated iteratively based on the input data and the desired output. The updates for different coefficients are often independent of each other. Parallel computing takes advantage of this independence by allowing multiple processors or threads to work on different coefficients simultaneously, avoiding the need for a sequential update of each coefficient.

-Parallelism in Matrix Operations:

Many adaptive filtering algorithms involve matrix operations, such as matrix multiplications and inversions. These operations can be parallelized, and modern parallel computing architectures, like multi-core processors or GPUs (Graphics Processing Units), can perform these operations concurrently.

Parallelism in matrix operations can significantly accelerate the computation of filter coefficients.

-Concurrent Processing for Large Datasets:

Adaptive filters often deal with large datasets, and the processing of each data point contributes to the update of filter coefficients. Parallel computing allows the simultaneous processing of multiple data points, distributing the computational load across multiple processing units. This is particularly beneficial in real-time applications where processing large datasets quickly is crucial.

-Reducing Convergence Time:

Adaptive filters aim to converge to an optimal set of coefficients that minimize the error between the filter output and the desired signal. Parallel computing can reduce the convergence time by updating coefficients concurrently, potentially reaching the optimal solution faster than a sequential approach.

-Efficient Utilization of Parallel Architectures:

Modern computing architectures often include multiple processing units, such as multi-core CPUs or GPUs. Parallel computing is designed to efficiently utilize these resources. Adaptive filter algorithms can be parallelized to take advantage of these architectures, leading to improved processing times.

-Scalability:

As the computational requirements increase with the complexity of the adaptive filter or the size of the dataset, parallel computing offers scalability. Adding more processing units can provide a proportional increase in computational power, allowing the algorithm to handle larger datasets or more complex models.

-Adaptability to Real-Time Requirements:

In real-time applications, low latency is crucial. Parallel computing allows for faster updates of filter coefficients, making adaptive filter algorithms suitable for real-time processing where quick responses are essential.

So, the parallelization of adaptive filter algorithms facilitates concurrent updates of filter coefficients, taking advantage of the independence of these updates, parallelism in matrix operations, and efficient utilization of parallel architectures. This results in faster processing times, making adaptive filters well-suited for applications where timely and efficient processing of large datasets is required.

5. “Verified the accuracy of the FPGA outcomes by comparing them to the Matlab simulation results found in the current literature.” Please explain in detail why by comparing FPGA results with Matlab simulation results currently available in the literature. Please explain in detail why not by comparing FPGA results with experimental results.

Response: Authors are grateful to the reviewer for his/her valuable suggestion.

6. “The necessity for dynamic modification of this parameter, in particular, may have a significant influence on the algorithm’s adaption rate. The EFF-RLS approach is usually recognized as more computationally efficient when used to small to medium sized problems.” Please elaborate on why the EFF-RLS method is generally considered more computationally efficient when solving small to medium-sized problems.

Response: Authors are grateful to the reviewer for bringing out this point into their consideration.

Explanation:

The Exponential Forgetting Factor Recursive Least Squares (EFF-RLS) approach is often considered more computationally efficient, especially when applied to small to medium-sized problems. Here are several reasons why this may be the case:

-Exponential Forgetting Factor (λ):

The use of an exponential forgetting factor allows the EFF-RLS algorithm to assign less weight to older data, emphasizing more recent observations. This can be advantageous in small to medium-sized problems where maintaining a memory of past data may not be as critical, and a faster adaptation to changes in the system is desired.

-Memory Efficiency:

EFF-RLS is designed to be memory-efficient. The exponential forgetting factor reduces the impact of older data on the parameter estimation, allowing the algorithm to focus on the most relevant information. In small to medium-sized problems, where memory constraints may not be as severe, this efficiency can contribute to overall computational efficiency.

-Reduced Computational Overhead:

The emphasis on recent data points through the exponential forgetting factor contributes to a reduction in the computational overhead associated with managing and processing historical data. This reduction in overhead is particularly beneficial for small to medium-sized problems, where the dataset is not excessively large.

-Adaptive Parameter Modification:

The statement mentions the necessity for dynamic modification of a parameter, which likely refers to the tuning of the forgetting factor. EFF-RLS provides a mechanism for dynamic adaptation of the forgetting factor, allowing the algorithm to adjust its behaviour based on the evolving

characteristics of the data. This adaptability can be advantageous in situations where the system's dynamics change over time.

-Fast Adaptation Rate:

The exponential forgetting factor inherently provides a faster adaptation to changes in the underlying system. In small to medium-sized problems, where rapid adjustments to the system are often required, EFF-RLS can provide a quicker response compared to algorithms with a slower adaptation rate.

-Suitability for Dynamic Environments:

Small to medium-sized problems are often encountered in dynamic environments where the underlying system parameters may vary. EFF-RLS, with its ability to dynamically adjust the forgetting factor, is well-suited for such dynamic environments, contributing to its computational efficiency in these scenarios.

-Less Computational Complexity:

EFF-RLS may have less computational complexity compared to other recursive least squares approaches, making it more efficient for smaller problem sizes. This is particularly relevant when computational resources are limited, and a simpler yet effective algorithm is preferred.

The Exponential Forgetting Factor Recursive Least Squares approach is generally considered more computationally efficient for small to medium-sized problems due to its emphasis on recent data, memory efficiency, reduced computational overhead, adaptive parameter modification, fast adaptation rate, suitability for dynamic environments, and potentially lower computational complexity. These characteristics make EFF-RLS a suitable choice for scenarios where efficiency in terms of both computation and adaptation to changing conditions is crucial.