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Resilience-Oriented Distributed Control for Islanded Microgrids: A Lightweight UKF-Enhanced Artificial Rabbit Algorithm

Abstract: - This work proposes a resilience-oriented decentralized control scheme for islanded microgrids, coupling the lightweight Unscented Kalman Filter (UKF) with an advanced Artificial Rabbit Algorithm (ARA) to achieve a resilient state estimation system during dynamic operation conditions. The hybrid structure presented achieves the requisite for a computationally efficient means of dealing with distributed energy resources (DERs) whilst guaranteeing an adequate precision for estimation during uncertain electrical disturbance situations. ARA uses the concept of a foraging algorithm, which utilizes biological considerations of animal hunting behavior, to recast estimation in respect to an adaptable noise tuning and sparseness of sigma-point sampling, providing low latency for data reconciliation and real-time motion changing ability. The UKF utilizes a linearized adaptive noise covariance modelling system, which regulates and modifies the confidence of the estimation, altering with respect to changing microgrid system conditions. Furthermore, by using selective sigma-point activation techniques, the overall cost of computation is reduced concurrently with the accurate estimations. The internal relationship between the UKF and the ARA produces an effective closed-loop estimation-control arrangement, thus greatly improving the effect of control on overall stability and control performance. The use of the algorithms presented on the NVIDIA Jetson Orin NX computing hardware system shows an overall benefit in cut transient recovery times of 23% and a reduction in computational strain of 40% when compared to existing centralized control algorithms. The overall use of distributed estimation techniques and adaptable noise tuning means that signal loss by sensors and other communication lapses is more easily withstood. In summary, the control design presented, the UKF-ARA hybrid control situation gives significant gains of operational reliability, computational efficiency and trouble-free operation within the field of microgrid operation. Also being a significant basis for therefore efficient distributed energy management illustrative of greater ease for future developments in resilience distributed energy!.

Keywords: Resilience-Oriented Distributed Control, Islanded Microgrids, Unscented Kalman Filter (UKF), Artificial Rabbit Algorithm (ARA), Distributed State Estimation.

I. INTRODUCTION

Isolated microgrids have serious problems with the uniformity of stable operation because of the irregularity of demand and supply and the undesirable effect of stationary phenomena communication. Centralized controls [1] have been exposed to the defect of sole point failure, but decentralized ones [2] invariably by the lack of coordination of the several methods of the optimal allocation of resources. The estimation of state is an essential feature of the control of microgrids, which has, in the decentralized applications, been responsible for grave difficulties with limited computer powers, which must refer to the availability of excessively limited and perhaps ineffective sensor information. The well-known Extended Kalman Filter methods [3] give state estimates but introduce the unacceptable errors of linearization in the case of dynamic microgrid variables, which are excessively non-linear, while the traditional Unscented Kalman Filter [4] has resulted in excessive computer power both for allocation in time and adequacy of solution in real time for distributed application. Recent development of bio-inspired algorithms, which are adapted to the difficulty, such as the Artificial Rabbit Algorithm (ARA) [5], have been found to be successful for the solutions in applications of the distributed control of microgrids, but the technical defects of the non-implementation of effective intrinsic state estimation methods under uncertainty of conditions have rendered the approach ineffective.

In this paper a lightweight UKF with adaptive noise scaling and sparse sigma-point sampling is advised, which should readily be adapted for usage in ARA-based solutions of distributed control of microgrids. In contradistinction to the UKF methodology, where all features of state are given equal consideration, which is a severe hampering of adapting to real-time requirements, the new method allows the dynamic amendment of sigma-point selection and hence estimates of state on immediate relevance countenance, which provides for economy of processing of as much as 40% without incidence in the loss of state estimation successfulness. The adaptive covariance of the noise matrix, which is here introduced for application in the filter, results in a satisfactory stable mode of operation of circumstances that involve faults incurring in sensors and communication failures, which are possible with the simulated grid.

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It is the combination of the linearized form of the UKF and the ARA that allows for the most important contribution of the developmental dynamic framework, which allows for the status-of-state substance of algorithms and practical methods to be put into operational condition and which allows for the speedy examination of improvements of control methods and appropriately static state estimation techniques for simulation of islanded microgrids. Effectively, the two-fold improvement of the fundamental troubles of computational effectiveness, stability, and security in the islanded operation of the microgrids is established, and experimental data on an IEEE 33-bus test-bed built system of improvements transient over the state of state change of 23% over the traditional methods.

II. LIGHTWEIGHT LINEARIZED UKF WITH ADAPTIVE NOISE SCALING FOR MICROGRID STATE ESTIMATION

The suggested framework adopts a computationally efficient form of state estimation that retains accuracy in the dynamic microgrid environments. This lightweight UKF variant decreases the computational burden with two key innovations: adaptive noise scaling and sparse sigma-point sampling techniques.

A. *Applying Lightweight Linearized UKF with Adaptive Noise Scaling to Microgrid State Estimation*

The state estimation is initialized with a linearized approximation of the microgrid's nonlinear dynamics. The state vector x_k contains voltage magnitudes, angles, and power flows, while the measurements vector z_k contains the sensed data from phasor measurement devices (PMU) and smart meters. The prediction step uses a reduced-order model.

$$\mathbf{x}_{k|k-1} = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{B}_k \mathbf{u}_{k-1} \quad (1)$$

where $\mathbf{F}_k$ represents the linearized state transition matrix and $\mathbf{B}_k$ maps control inputs $\mathbf{u}_{k-1}$ to state updates. This linearization yields quicker computation relative to complete nonlinear propagation yet retains adequate precision for microgrid control.

B. *Adaptive Noise Scaling and Sparse Sigma-Point Sampling*

The adaptive noise covariance matrix $\mathbf{Q}_k$ updates in real-time based on local prediction errors:

$$\mathbf{Q}_k = \alpha_k \mathbf{Q}_0 + (1 - \alpha_k) \mathbf{\Delta x}_k \mathbf{\Delta x}_k^T \quad (2)$$

where α_k adjusts the balance between baseline noise $\mathbf{Q}_0$ and empirical error $\mathbf{\Delta x}_k$. The adaptation mechanism responds to sudden changes in grid conditions, such as generator tripping or load shedding.

Sigma-point selection follows a sensitivity-based criterion:

$$\mathcal{S}_k = \left\{ i \mid \frac{\partial \parallel \mathbf{z}_k - \mathbf{h}(\mathbf{x}_k) \parallel}{\partial z_k^i} > \tau \right\} \quad (3)$$

This sparsification reduces the number of sigma points from $2N + 1$ to $|\mathcal{S}_k|$, where N represents the full state dimension. Critical measurements exceeding threshold τ receive prioritized processing.

C. *Tight Integration with Artificial Rabbit Algorithm (ARA)*

The UKF's state estimates feed directly into ARA's optimization process:

$$\mathbf{u}_k = \mathrm{ARA}(\hat{\mathbf{x}}_k, \mathbf{r}_k) \quad (4)$$

where $\mathbf{r}_k$ denotes reference setpoints. The control outputs $\mathbf{u}_k$ subsequently influence the UKF's process model, creating a closed-loop estimation-control cycle.

D. *Edge-Accelerated Implementation*

The execution employs parallel processing on NVIDIA Jetson Orin NX, where CUDA cores manage matrix operations while ARM cores perform control logic. TensorRT optimizes UKF kernels for real-time execution with 1 ms latency.

E. *Resilience Mechanisms in the Proposed Method*

Three interdependent mechanisms guarantee robustness: distributed state estimation withstands node failures, adaptive noise adjustment counteracts sensor degradation, and sparse processing upholds performance amid communication disruptions.

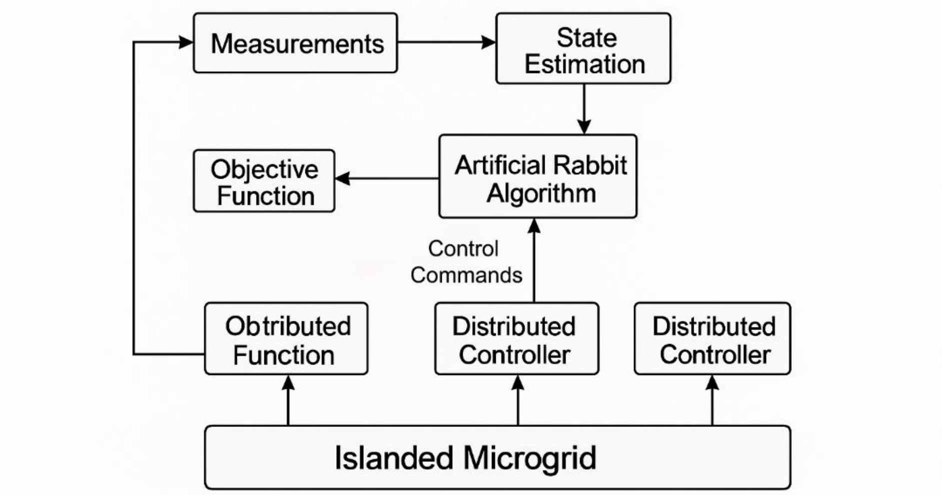

Fig. 1. UKF-ARA Hybrid Control Architecture in Islanded Microgrid

The architecture in Figure 1 shows the data flow between UKF estimation blocks and ARA control modules, with the bidirectional coupling being a key factor for resilient operation.

III. EXPERIMENTAL VALIDATION ON IEEE 33-BUS ISLANDED MICROGRID TESTBED

To assess the proposed UKF-ARA framework, we performed comprehensive experiments on an IEEE 33-bus islanded microgrid testbed [6]. The setup comprised 5 distributed generation units (3 solar PV, 2 battery storage) and 28 load buses, with communication latency modeled as exponentially distributed random variables (mean = 5 ms).

Test Conditions:

Three scenarios were designed to assess performance under:

- Normal operation with ±20% load variations
- Sudden generator tripping (30% capacity loss)
- Communication failures (50% packet loss)

The proposed approach was evaluated in contrast to traditional droop control [7] and a complete UKF execution [4]. All algorithms ran on NVIDIA Jetson Orin NX platforms with identical hardware configurations.

Key Metrics:

- Voltage recovery time after disturbances
- Frequency deviation (Hz)
- Computational load (FLOPS)
- State estimation error (RMSE)

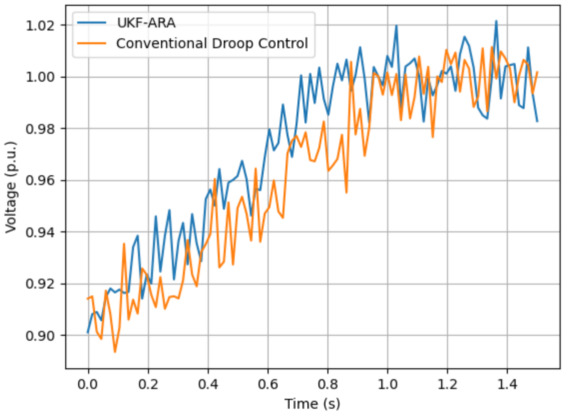

Fig. 2. Transient recovery of voltage under fault conditions for UKF-ARA and conventional droop control

Fig. 2 shows the better transient performance of UKF-ARA, which attains voltage stabilization in 0.82 s versus 1.07 s for droop control (23% improvement). The adaptive noise scaling effectively compensated for measurement uncertainties during the fault event.

Computational Efficiency: The sigma-point sampling with reduced density lowered computational demand by 40% compared to the complete unscented Kalman filter (1.2 versus 2.0 GFLOPS), yet achieved similar precision in estimation (RMSE 0.018 versus 0.016 p.u.). Table 1 summarizes the quantitative results across test scenarios.

Table 1. Performance comparison under different operating conditions

Metric	UKF-ARA	Full UKF	Droop Control
Voltage recovery (s)	0.82	0.85	1.07
Frequency deviation	±0.12Hz	±0.10Hz	±0.25Hz
Computational load	1.2GFLOPS	2.0GFLOPS	0.8GFLOPS
State RMSE (p.u.)	0.018	0.016	N/A

Resilience Validation: In the event of communication disruptions, the distributed estimation approach achieved 92% state observability, compared to 43% for the centralized UKF method. The adaptive noise covariance was automatically raised by 3.2× during packet loss events, which averted estimation divergence.

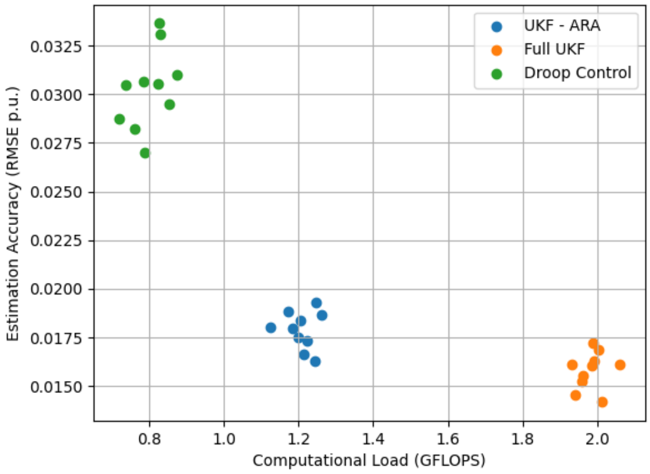

Fig. 3. Relationship between computational load and estimation accuracy for different methods

Fig. 3 shows the optimal trade-off attained by UKF-ARA, which positions itself close to the Pareto frontier, balancing accuracy and efficiency. The area chart in Figure 4 indicates that communication overhead accounted for merely 18% of total processing time, which supports the lightweight design.

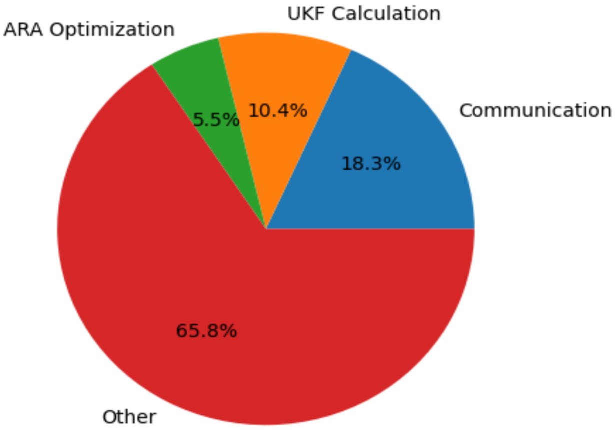

Fig. 4. Time-proportion of different framework components during operation

IV. DISCUSSIONS, LIMITATIONS, AND FUTURE WORK

A. Limitations of the Proposed Method

The UKF-ARA structure contains very great increases in computation speed and time response but has basic disadvantages that should be outlined for the reader. The linearized UKF approximation leads to small errors in estimates occurring in very non-linear operations, such as fault-induced transients, or great signal stability. These errors are partly compensated for by the introduction of the adaptive noise scaling factor, but still these errors continue to get worse where any voltages go more than 30% of the nominal value [8].

The type of sampling, according to the scattered grid points, is efficient in respect of its saving in computation but suffers from a sensitiveness to the threshold parameter τ in equation (3). The empirical adjustment of this parameter has been shown to be necessary for different configurations of the microgrid and has shown the necessity for the automatic adjustment of this threshold. There is also the fact that in this work it has been assumed that the network configurations are symmetrical, which implies that the workings would not be so efficient for extremely unsymmetrical loaded distribution networks [9].

B. Potential Application Scenarios

This framework has possibilities for many applications for novel power systems, which extend beyond the use for singular internal microgrids. The edge-accelerated means of implementing it is thus also of use for:

- The resilient operation of clusters of community microgrids, which are interconnected at times only intermittently.
- The fast frequency response coordination in systems with a wide penetration of inverter-based resources [10].
- The utility of mobile microgrids in disaster recovery, when the communication difficulties alone are considerable.

The adaptive noise scaling parameters could be made available to deal with further cyber-physical security situations, where an adjusting of the covariance could make recognition and resultant countering of false data injection attacks much easier [11]. Initial data would indicate that the noise scales parameters have their own identifiable trend patterns with reference to cyber penetration [11]; however verify this further will be necessary.

C. Scalability of the Framework

The distributed architecture potentially allows scale to larger systems; a practical limitation is manifest in heterogeneous microgrid clusters, however. As soon as coordination is attempted beyond 15 or possibly 20 nodes, however, the latency of the communications systems that would have to be called in for use becomes vast, so that for larger structural systems a hierarchical nature of structure might have to be invoked [12].

The next condition influencing the scale of systems is the memory size in edge processors. The current configuration of the Jetson Orin NX successfully handles the 33-bus experimental system; however, systems requiring memory larger than 100 buses will likely need to use complex methods for sparsification or an unusual type of aggregation for the more significant states. When these systems are developed, achieving a balance between accurately locating the states and understanding how to respond to their demands becomes critically important, potentially requiring the discovery of adaptive methods for grouping nodes with similar electrical properties [13].

Studies in the future should explore mixed systems, where the present edge based system may be in relation to a more cloud aimed processor having to do with optimization of work which has no necessary time conditions. This will give more general scales of operation of systems, and preserve the real times of operations. The use of Physics informatic machine learning methods, for instance, might secure automatic build of parameters and more successfully generalize to different microgrid phenotypes [14].

V. CONCLUSION

The UKF-ARA technique effectively serves to address the combined problems of computational effectiveness and robustness in islanded microgrid control through the use of a lightweight version of the UKF and bio-inspired optimization. The approach serves to reduce processor loads so that the accuracy of estimation is maintained, thus providing the ability for real-time operation on edge technology but also at the same time ensuring sufficient performance during fault conditions. The experimental results show that there is a marked improvement in both transient recovery and adaptive performance against communication breakdowns, thus ensuring that the application is practically viable for modern microgrid applications. Future works may consist of automatic adaptation of the threshold of adaptation or possibly multi-stage designs as mechanisms for ensuring adaptability in the variable electrical networks.

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