Conceptual Design of an Online Estimation System for Stigmergic Collaboration and Nodal Intelligence on Distributed DC Systems

Wesley DOORSAMY[1], Willem CRONJE[2]
[1]*School of Electrical and Electronic Engineering, University of Johannesburg, South Africa*
[2]*School of Electrical and Information Engineering, University of the Witwatersrand, South Africa*
za.wesley.doorsamy@ieee.org; wacronje@ieee.org

***Abstract*—The secondary level control of stand-alone distributed energy systems requires accurate online state information for effective coordination of its components. State estimation is possible through several techniques depending on the system's architecture and control philosophy. A conceptual design of an online state estimation system to provide nodal autonomy on DC systems is presented. The proposed estimation system uses local measurements - at each node - to obtain an aggregation of the system's state required for nodal self-control without the need for external communication with other nodes or a central controller. The recursive least-squares technique is used in conjunction with stigmergic collaboration to implement the state estimation system. Numerical results are obtained using a Matlab/Simulink model and experimentally validated in a laboratory setting. Results indicate that the proposed system provides accurate estimation and fast updating during both quasi-static and transient states.**

***Index Terms*—autonomous agents, distributed energy systems, microgrid, recursive estimation, state estimation.**

I. INTRODUCTION

Distributed energy systems (DES's) are becoming increasingly popular worldwide as power generation undergoes a paradigm shift from centralized to more distributed schemes [1]. Grid-connected systems can offer improved reliability and power quality through integrating distributed generation and providing islanding capability [2, 3]. Additionally, stand-alone systems can be implemented for remote, rural and other specialized applications where no grid connection is available [4]. There are several types of architectures and control strategies depending on the type of application. In many of these cases, state information is essential for coordinating the system components to successfully balance local supply and demand. A conceptual design of an online state estimation system which supports nodal autonomy is presented. The proposed estimation system makes accurate online estimates of a distributed system available at each node. This allows for each source, storage and load node to effectively control itself without communicating with other nodes or receiving instructions from a centralized control system. The initial concept of the estimation system for autonomous nodes in DESs was first presented in [5]. The presented research builds on this concept with substantial improvements to the design, model implementation, testing and experimental validation of the estimation system. Additionally, the implementation of stigmergic mechanisms in state estimation to achieve nodal collaboration without requiring communications – to the best of the authors' knowledge - has not yet been presented and will potentially contribute to the design of parsimonious state estimation systems. This paper is organized as follows. The concepts of DESs and distributed intelligence are discussed in Section II and III, respectively. Section IV describes the estimation methodology. Results from the simulation model testing are then presented in Section V followed by the experimental validation in Section VI. Finally, a brief summary of the research is given.

II. STAND-ALONE DISTRIBUTED ENERGY SYSTEMS

DESs comprise energy resources (microturbines, fuel cells, photovoltaics, etc.) together with storage devices (flywheels, energy capacitors and batteries) and flexible loads [6]. The term "Distributed Resource Island" is also used to unambiguously describe these systems [7]. These systems can be operated in a non-autonomous way, when interconnected to the main grid, or in an autonomous way, if disconnected from the grid [6]. A grid-connected system can operate in an 'Islanded mode' by temporarily disconnecting from the grid. However, many applications require off-grid systems which are completely autonomous and stand-alone. Stand-alone DESs can be deployed in remote areas where grid-extension is not feasible such as islands and rural communities [4, 8], and are also gaining interest in marine, aerospace, electric vehicle, telecommunications and other industrial applications [9, 10].

This research focuses on stand-alone or autonomously operating systems. Moreover, the proposed estimation system is intended for low-voltage, low-power DC applications. DC DESs are growing in popularity as it facilitates integration of distributed generation systems due to inherent compliance with modern DC input-type electronic loads, DC output-type renewable energy sources and storage devices [11, 12].

III. DISTRIBUTED INTELLIGENCE

A. Nodal Autonomy

An autonomous system is a system which has the power and ability to self-govern. Most grid-connected systems are designed to disconnect and operate autonomously which improves the overall integrity of the both the grid and DES. A typical stand-alone distributed system is autonomous but does not contain autonomous entities and is therefore reliant

Digital Object Identifier 10.4316/AECE.2017.02007

on a central control system which communicates with individual nodes and has complete knowledge of the system. The system is therefore limited in scalability and is vulnerable to malfunction when the central controller faults. This research proposes an additional degree of autonomy distributed at the nodal level in order to improve overall system integrity, robustness and scalability by eliminating the need for a central controller and communications across the network. An autonomous system requires the necessary controller which gives it the ability and power to self-govern. In addition to the actual controller, the system requires adequate environmental perception or, in this case, state estimation. Fig. 1 shows how the estimation and control is distributed among the source, load and storage type nodes. Each node is equipped with independent estimation and control, and the system's operation is managed through the coordinated effort of these nodes. In this way, the system may be viewed as a multi-agent system where the computational components are autonomous with local goals collectively achieving the intended operation of the overall system [5].

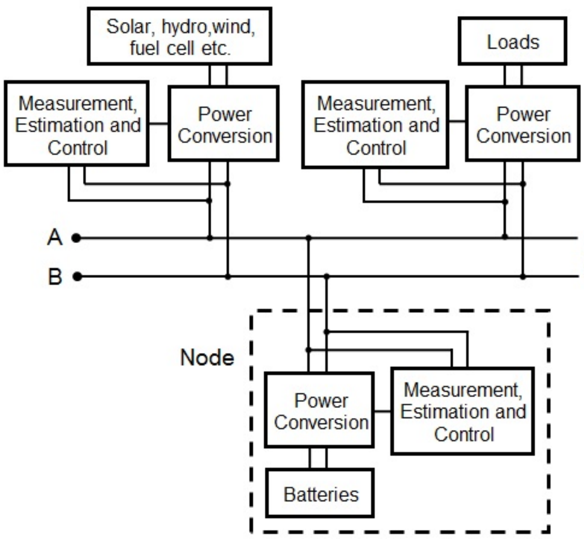

Figure 1. Stand-alone distributed DC system with autonomous storage, load and source nodes equipped with local estimation and control

B. Online State Estimation

The present state of a system may be considered as the minimal amount of past information required to completely describe the future behavior - or outputs - of the system [13]. The Thevenin equivalent parameters of a power system are time dependent and represent an aggregation of the system's operating conditions and can therefore be considered as the state variables [14]. In fact, the control components of many power systems which require distributed intelligence utilize Thevenin equivalent parameters as an indication of the state of the system [15, 16]. The presented estimation system aims to determine the Thevenin equivalent parameters - as 'seen' by each node - in order to ascertain the state of the rest of the system. This enables each autonomous node to act accordingly with the purpose of maintaining the overall integrity of the system - e.g. a non-critical load node may temporarily disconnect when under strain or a storage node may absorb excess generation when necessary. Online estimation utilizes the available measurements to determine the present state of the system [17]. Since the proposed system does not have a direct interface and information transfer between nodes or a central control system, the only measurements available to the node are local. The estimation system of a node therefore uses the local current and voltage measurement to estimate the Thevenin equivalent parameters – as observed by that specific node – of the rest of the system. Fig. 2 gives the Thevenin equivalent model of the DC system as observed by a node.

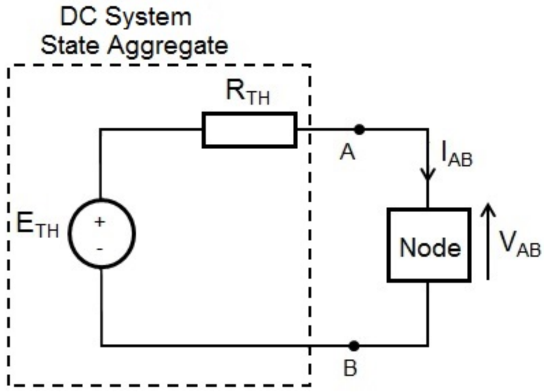

Figure 2. Thevenin equivalent model of the stand-alone DC system - as observed by a single node - represents an aggregation of the system's state

Applying Kirchoff's Voltage Law (KVL) to the equivalent circuit shown in Fig. 2 yields the expression given in (1).

$$E_{TH} = I_{AB} R_{TH} + V_{AB} \tag{1}$$

The Thevenin voltage (E_{TH}) and resistance (R_{TH}) in (1) are unknown, and the node voltage (V_{AB}) and current (I_{AB}) are available through measurement. Solving for the unknown Thevenin parameters (contained in matrix X) and parametrizing (1) into a discrete form (with sample number k) gives:

$$Y_k = H_k \times X_k \tag{2}$$

where,

$$X_k = \begin{pmatrix} E_{TH,k} \\ R_{TH,k} \end{pmatrix} ;\ Y_k = V_{AB,k}\ ;\ H_k = \begin{pmatrix} 1 & -I_{AB,k} \end{pmatrix} \tag{3}$$

IV. Methodology

A. Classical Recursive Least-Squares Technique

The RLS method is used to assess the best estimates of the unknowns taking into account new measurements, given the initialization parameters. The following equations are applied to (2):

$$K_k = P_{k-1} H_k \left(\lambda I + H_k^T P_{k-1} H_k \right)^{-1} \tag{4}$$

$$P_k = \frac{1}{\lambda} \left(I - K_k H_k^T \right) P_{k-1} \tag{5}$$

$$X_k = X_{k-1} + K_k \left(Y_k - H_k^T X_{k-1} \right) \tag{6}$$

where I is the identity matrix, λ is the forgetting factor, P is the covariance matrix, and K is the gain [18]. The standard recursive least squares estimation (RLSE) routine is intended for estimation when the target parameters remain constant and it therefore has poor tracking performance. Additionally, if the new measurements are constant, accurate convergence to the target estimate is not achieved. A number of different extensions of the standard RLSE are used to overcome these issues in practice. The presented algorithm extends on the standard RLSE method by providing covariance resetting and controlled excitation. Resetting the covariance limits the memory of the routine and allows it to react to more rapid variations in the environment including sudden appearance of an interferer [19]. Whenever there are significant changes in the targeted parameters, the online system will continuously remove past estimates and provide new updated estimates. A controlled excitation or perturbation of the input parameters is used to obtain a suitable variation in the node measurements thus ensuring convergence and improving accuracy.

B. Extended Recursive Least-Squares with Perturbation

The controlled-excitation extension of the RLSE algorithm ensures that there is convergence when there is a change in the targeted Thevenin parameters. Physical excitation can be achieved in two ways: actively or passively. Active perturbation uses an additional source of energy to obtain a suitable variation in the node measurement. More commonly, estimation systems of components of renewable energy sources (such as inverters) utilising active current-injection methods have been proposed [20, 21]. The technique presented here is passive and uses a perturbation resistor (shown in Fig. 3), to achieve the same variation at the node of interest. Fig. 3 also shows the timing used for the covariance resetting and estimate storing in relation to the switching method.

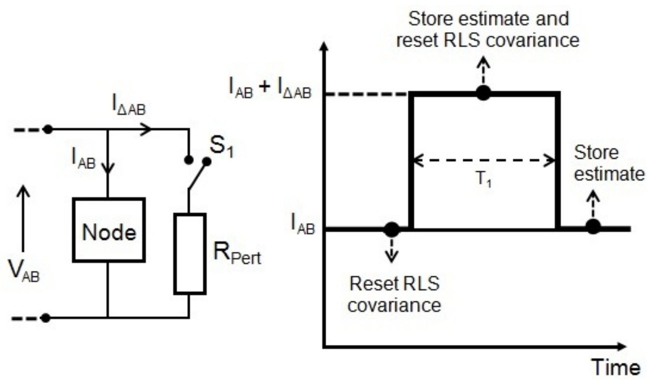

Figure 3. Passive perturbation technique used for controlled excitation and dynamic tracking of Thevenin parameters

There are two types of triggers that initiate these controlled perturbations i.e. Type 1 and 2. In the first instance, a perturbation is triggered periodically for regular updating of the estimate and accounts for any relatively slow drift in the target parameters (quasi-static state). Type 2 is a rapid change in the node measurements which indicates a change in the targeted parameters (transient state).

C. Stigmergic Collaboration

The field of biomimetics deals with the study and imitation of nature's designs, methods and processes, and is becoming increasingly involved with emerging subjects of science and engineering [22]. An example is the use of social systems in nature for the development of distributed artificial intelligence [23]. Social insect colonies - although comprising very simple individual organisms with limited capabilities - can perform highly complex tasks with a high degree of flexibility and robustness in a dynamic environment [24]. The presented concept for intelligent nodes on autonomous DC systems takes inspiration from social insect behaviour. Each node performs its assigned task in collaboration with other nodes to fulfil the overall goals of the system. The envisaged autonomous DES will mimic social insect behaviour in that each node performs a specific set of tasks without instructions (control signals) from a central controller.

The presented state estimation system is based on the concept of stigmergic collaboration. Stigmergy is a class of self-organising behaviour whereby collective activity is coordinated by each agent's response to and modification of its local environment [25]. The estimation system similarly enables each intelligent node to self-organise in a coordinated way using the state it perceives through locally measured parameters (V_{AB} and I_{AB}). Furthermore, each intelligent node can recognise intentional modification of the environment - i.e. perturbation - by another node and responds appropriately. This stigmergic agent-based estimation system offers the following benefits:

- More simple agents are used instead of a single complex agent that decreases the overall complexity of the system. The reliance on a single controlling entity is eliminated thereby decreasing the likelihood of catastrophic failure.
- The internal state of each agent does not need to be directly known by another agent, or by a single controlling agent, thus eliminating the need for related infrastructure.
- System-level outcomes may be achieved through sub-system tasks which improves modularity, scalability, flexibility and robustness.
- Potential use in any application requiring distributed intelligence (with or without stigmergic collaboration), where Thevenin parameters constitute adequate information for effective control.

V. SIMULATION TESTING

A. Estimation System Performance

The fundamental method for calculating the Thevenin equivalent of an unknown circuit, in this case the distributed system, is to obtain the open circuit voltage and short circuit current. This is not feasible for online application as it is intrusive, unsafe and potentially catastrophic to the system. Instead, the proposed estimation system determines the Thevenin parameters of the system, as seen by a specific node, while it is in operation. However, as previously mentioned, controlled excitation is required to intentionally vary node measurements. It is therefore critical to obtain a suitable level of perturbation that is non-intrusive to the system, sustainable and parsimonious in its energy consumption. Simulation testing is carried out here to determine the properties of the perturbation and its effects on the accuracy of the state estimate. The error of the estimation system is defined as the difference between estimates (V_{TH} and R_{TH}) and the actual Thevenin equivalent parameters. The controlled perturbation is achieved on the actual system by varying the total current flowing in or out (depending on node type) by switching in a resistance (R_{Pert}), as show in Fig. 3. For the purpose of generalization, the perturbation parameter (x_I) is defined here as the ratio of the change in the node current ($I_{\Delta AB}$) and the node current (I_{AB}). Similarly, the perturbation parameter for voltage is defined as x_V. The objective of optimising the estimation accuracy is to minimise the error function, which is dependent on the perturbation parameter (x) and measurement error (σ) as given by

$$\min E(x,\sigma)$$

where the error function is the sum of the squares of the difference between the estimated parameters and the target parameters as follows:

$$E(x,\sigma)=\left(\tilde{V}_{TH}(x,\sigma)-V_{TH}\right)^2 + \left(\tilde{R}_{TH}(x,\sigma)-R_{TH}\right)^2 \tag{7}$$

Although the presented problem has a large number of interdependencies, the objective function captures the system in its entirety by resolving the accuracy of the estimate by focusing on inputs x and σ. Simply put, the accuracy of the estimation ultimately depends on these parameters, namely, the intentional perturbation and the measurement (node voltage and current) uncertainty. A contrived set of internal system parameters are used with the aim of understanding the conditions for perturbation optimality. While the error function, given by (8), may have a quantifiable minimum - the physical constraints of the system excludes a variety of possible minima. Hence, the optimisation procedure here requires a more physical interpretation rather than seeking a mathematical minimum. A simulation model of the circuit shown in Fig. 3 is constructed in Simulink with V_{TH}, R_{TH} and load node resistance R_{Node} fixed at 15V, 50Ω, and 50Ω respectively. The parameter R_{Pert} is varied to obtain different levels of perturbation x, and σ is the noise added to the measurements V_{AB} and I_{AB}.

Fig. 4 gives an example of the node measurements (without measurement error) during a single perturbation. Fig. 5 shows the simulation results for the effects of the perturbation parameter on the accuracy of estimation system, for a fixed level of measurement noise. This result shows that a mathematical minimum exists but physically this corresponds to a short circuit across the node terminals which is highly intrusive and potentially catastrophic. Therefore, selection of the optimal perturbation parameter is based on the operational criteria or specifications of the distributed system - e.g. voltage perturbation parameter must be less than 10%.

The measurement uncertainty is the other significant parameter which affects the estimation accuracy. In practice, there will be a limitation on accuracy of the supply and the measurement instruments on the system. For test purposes, noise is added to the simulated measurements and represents the compounded effects of the total uncertainty.

The graphs of different levels of measurement noise, corresponding to different levels of uncertainty, are given in Fig. 6. In each instance, the accuracy of the estimation system is simulated for a range of perturbation levels (only the voltage perturbation parameter is presented). These graphs indicate that higher levels of uncertainty require relative increases in the voltage perturbation parameter to maintain a specific level of estimation accuracy.

B. Nodal Collaboration

The collaboration function of the estimation system gives an intelligent node the ability to independently estimate Thevenin parameters. The estimation algorithm uses a subroutine to distinguish the controlled perturbations (with a unique duration and amplitude) initiated by another node from variations in the targeted parameters. A simple two load-node scenario is simulated to test this collaboration concept.

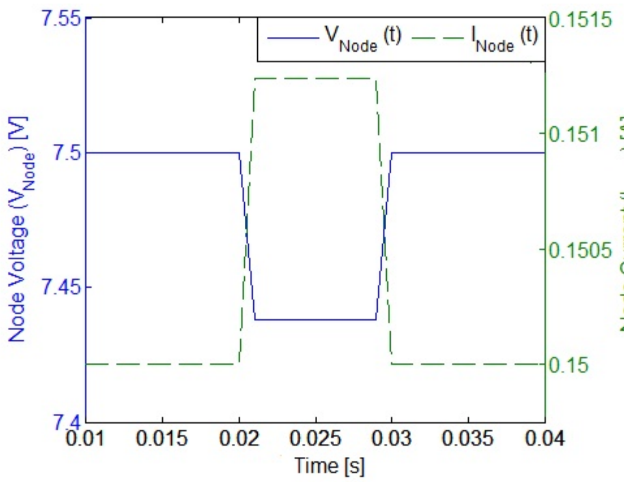

Figure 4. Example of simulated node measurements during perturbation (without additive noise)

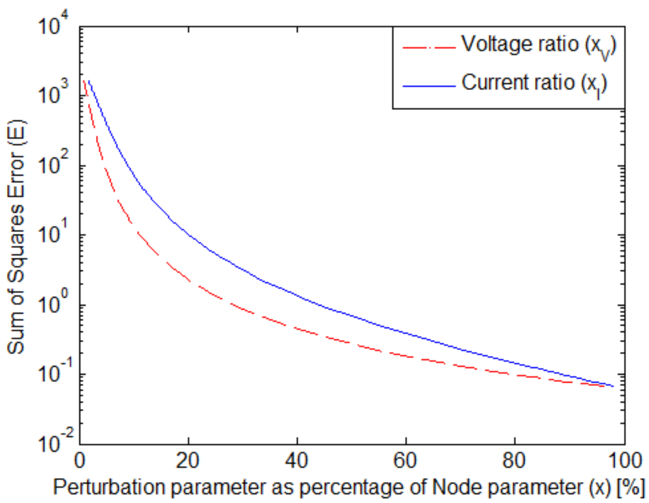

Figure 5. Example of simulated node measurements during perturbation (with constant additive noise of σ_{psd} = 1e-9W)

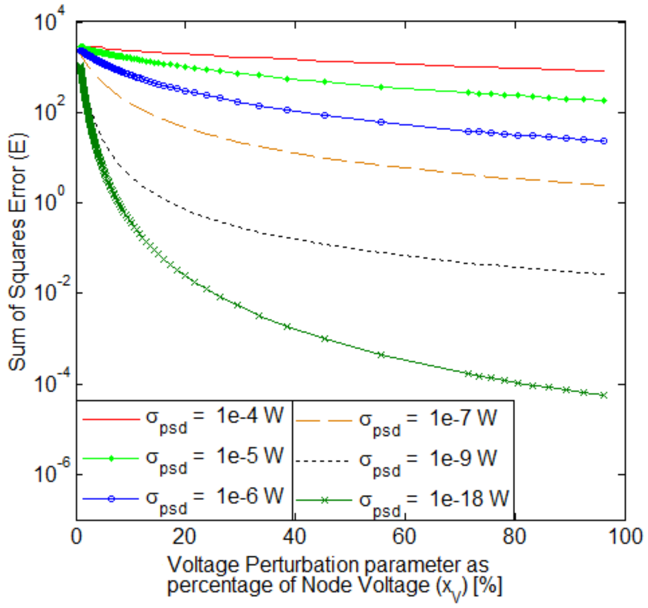

Figure 6. Simulated estimator performance with varying voltage perturbation parameter for different levels of uncertainty

A similar circuit configuration to the single node scenario is used together with an additional source resistance and load node. The circuit parameters V_S, R_S, R_{Node1} and R_{Node2} are 18V, 250Ω, 200Ω, and 100Ω, respectively. In this scenario, the Thevenin equivalent voltage and resistance 'seen' by each node differs ($V_{THnode1}$ = 5.14V, $R_{THnode1}$ = 71.43Ω, and $V_{THnode2}$ = 8V, $R_{THnode1}$ = 111.11Ω).

Fig. 7 shows the results of the simulated estimator performance in determining the Thevenin voltages. The voltage source is stepped from 18V to 28V after 5 seconds, which means that the Thevenin voltage 'seen' by each node changes to $V_{THnode1}$ = 8V and $V_{THnode2}$ = 12.44V. The figure shows that each node accurately estimates these new Thevenin voltages. It is again highlighted that the focus of the paper is on the estimation system and not on a specific DES application. Therefore, physical limitations of the estimation system such as the maximum number of nodes that can be supported are not addressed here.

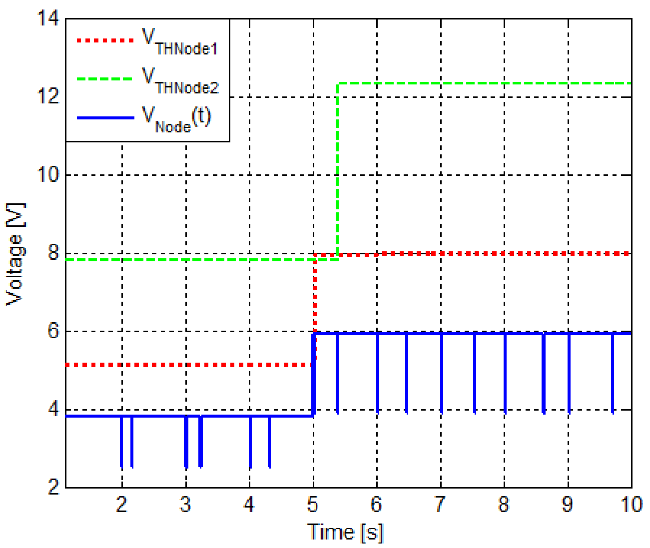

Figure 7. Simulated performance of estimators in tracking Thevenin equivalent voltages for a multiple node scenario, with corresponding node voltage

Differences in node types such as source and storage nodes will affect the direction of current flow - i.e. current flows either into (storage charging) or out of (source generating or storage discharging) the node. This directional difference is accounted for by the system parameter (H) containing the node current (I_{AB}) information.

VI. Experimental Validation

A. Test Circuits

Firstly, the extended RLSE algorithm is experimentally tested using the setup shown in figures 8 and 9. Fig. 8 shows the perturbation circuit used. The circuit consists of a switching circuit, snubber, digital input and accompanying isolation. This perturbation circuit has a modular design to enable use with a microcontroller. For the purpose of validating the algorithm, feedback and digital input to perturbation circuit are carried out using dSPACE. Firstly, a single load node scenario is used with a controllable voltage source and known resistances (preset to aforementioned simulation testing values). The estimation algorithm is implemented in Matlab Real-Time Interface (RTI) with dSPACE. Node measurements are read via the dSPACE analogue inputs. The digital output of the dSPACE controller board outputs the perturbation signal to the switching circuit. The collaboration function is experimentally validated using the same testing methodology but for a two node scenario - i.e. circuit parameters preset to those given in the corresponding simulation testing of the nodal collaboration.

B. Results

The results from two experimental performance tests – i.e. for single node and multinode cases are given in figures 10, 11 and 12. Fig. 10 shows the actual and estimated Thevenin voltages during a transient. The corresponding Thevenin resistance is given in Fig. 11. These results indicate that the proposed estimator is able to dynamically track the target parameters. Perturbations in the node current are also shown in Fig. 11. Relatively large (in magnitude) perturbations are required to achieve suitable accuracy due to inherent voltage source fluctuations and measurement error (no noise filtering performed). Fig. 12 shows the experimental performance of the estimator in tracking the Thevenin voltages when applied to a two-node case. This result corresponds to the simulated performance of the estimator given in Fig. 7. It can be seen that the parameter estimation occurs here under a type 1 trigger – i.e. regular period updating. This is a validation of how the algorithm can function independently (without communication) on two separate nodes.

A summary of the tracking accuracy for this case is also given in Table I. The mean percentage error (MPE) is given by the difference between the actual (A) and estimated ($\tilde{A}$) values of the targeted parameter, as shown in (9). Table I MPEs are measures of the total error and includes experimental error.

$$MPE = \frac{100\%}{n} \sum_{k=1}^{n} \frac{A_k - \tilde{A}_k}{A_k} \tag{8}$$

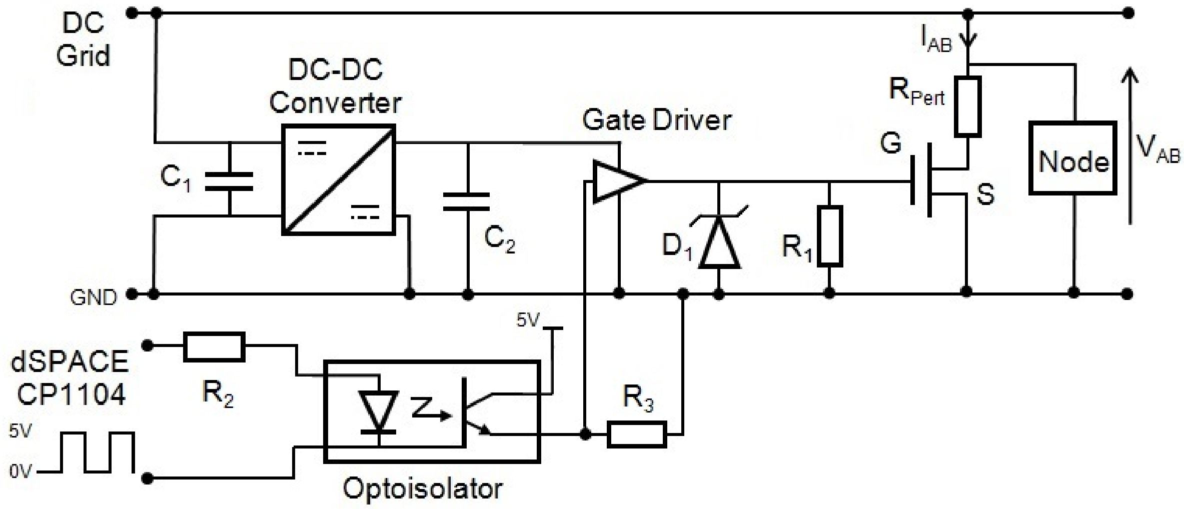

Figure 8. Switching circuit used for passive perturbation in the experimental validation of the estimation system

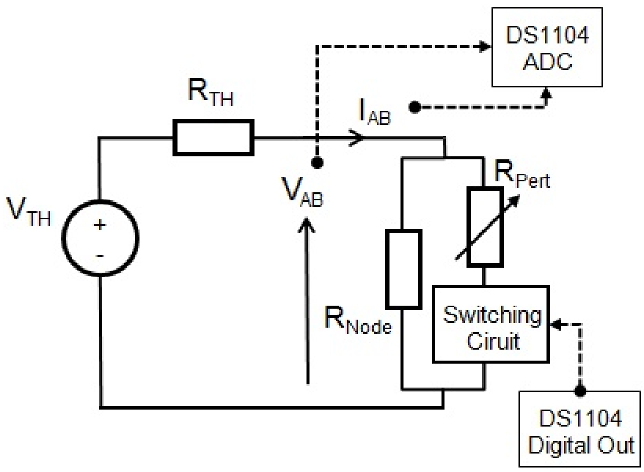

Figure 9. Overview of experimental configuration used for testing and validating the estimation system only

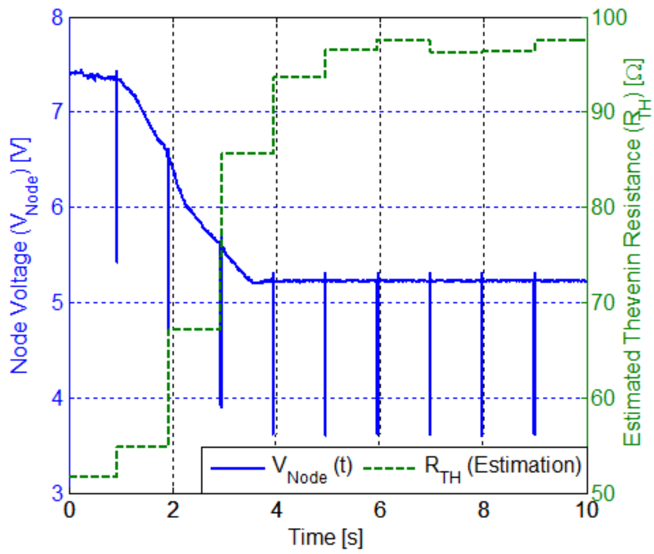

Figure 11. Experimental performance of on-line estimator in dynamically tracking Thevenin resistance during slow-transient and steady-state (quasi-static), and node voltage measurement consisting of perturbations

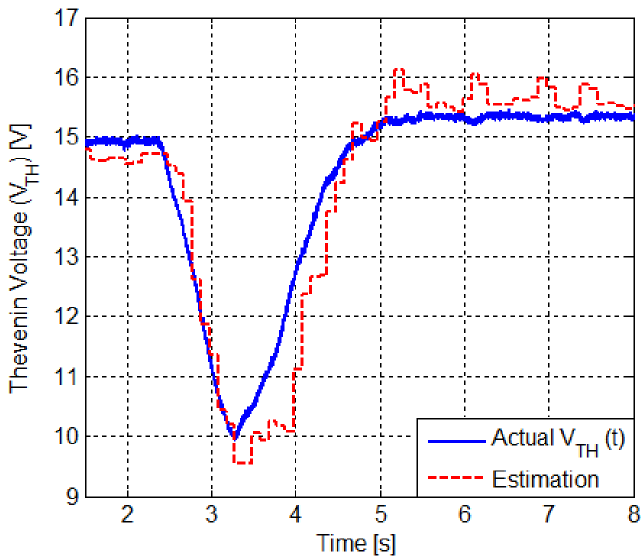

Figure 10. Experimental performance of on-line estimator in dynamically tracking Thevenin voltage during transient state

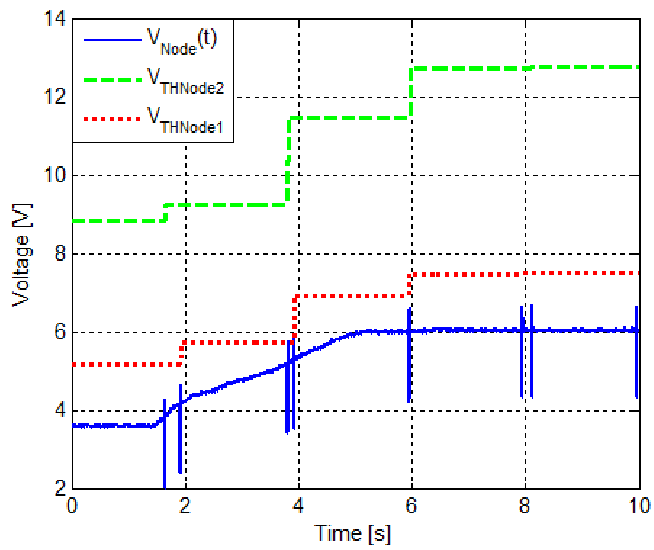

Figure 12. Experimental performance of on-line estimators, of two different nodes, in dynamically tracking Thevenin voltages during transient state

TABLE I. SUMMARY OF EXPERIMENTAL ESTIMATION PERFORMANCE FOR MULTI-NODE TEST CASE

Targeted Parameter	Mean Error (%)
$V_{THNode1}$	6.82
$V_{THNode2}$	6.10
$R_{THNode1}$	9.47
$R_{THNode2}$	7.66

VII. FUTURE WORK

The envisioned application area of the presented estimation system is stand-alone rural/remote DESs operating at lower power levels. These applications typically require low maintenance to maintenance-free, robust, self-configuring and scalable systems to supply mainly lighting and low power appliances. Since the presented investigation uses an experimental setup to validate the conceptual design of the estimation system – the next step of the work will be to design the parameters of perturbation technique based on extended RLSE method to function on a practical DES application. This will require an extensive study of the output impedance of switched DC/DC converters, as presented in [26]. Through considering a specific case study or application, the power capacity of the presented passive method can be specifically designed according to the power rating of the perturbated point. Sizing and timing of the perturbation signal is critical keeping in mind that many converters may regulate at high speeds causing attenuation to the perturbation. Additionally, understanding the practical implications of implementing the presented system requires further investigation of the varying impedance characteristics of converters in the frequency domain, as shown in [27]. Hence, future work will also look at how the passive perturbation method and extended RLSE can realize a wide frequency domain analysis.

VIII. CONCLUSION

DESs are becoming increasingly popular as a means of integrating distributed generation and can be implemented as stand-alone systems for remote, rural and other specialized applications where no grid connection is available. In order to provide the necessary reliability, robustness, scalability and operational flexibility required by these applications, this research proposes a state estimation system intended to support nodal autonomy on DC systems. The estimation system uses stigmergic collaboration and provides accurate state information, in the form of the Thevenin equivalent, without the need for a central controller using only local measurements. An on-line RLSE-based algorithm is used to determine the Thevenin equivalent parameters as an aggregation of the system's operating conditions so that it can act accordingly. The presented system employs a passive perturbation technique and covariance resetting to ensure solution convergence and improved estimation accuracy.

The estimation system was successfully simulated in Matlab/Simulink and experimental validated in a laboratory setting. An optimization study was carried out for a single-node case to determine the effects of noise and perturbation characteristics on the performance of the estimation system. A multi-node implementation of the estimation system was also simulated and experimentally validated in order to verify the stigmergic collaboration capabilities of the estimation system.

APPENDIX A

Thevenin equivalents and node voltage for two-node scenario:

$$V_{THNode1} = \frac{V_S R_{Node2}}{R_{Node2} + R_S} \tag{9}$$

$$R_{THNode1} = \frac{R_S R_{Node2}}{R_{Node2} + R_S} \tag{10}$$

$$V_{THNode2} = \frac{V_S R_{Node1}}{R_{Node1} + R_S} \tag{11}$$

$$R_{THNode2} = \frac{R_S R_{Node1}}{R_{Node1} + R_S} \tag{12}$$

$$R_{Node//} = \frac{R_{Node1} R_{Node2}}{R_{Node1} + R_{Node2}} \tag{13}$$

$$V_{Node} = \frac{V_S R_{Node//}}{R_S + R_{Node//}} \tag{14}$$

REFERENCES

[1] X. Wang, J. M. Guerrero, F. Blaabjerg, and Z. Chen, "A review of power electronics based microgrids", Journal of Power Electronics, Vol. 12, No. 1, pp. 181-192, January 2012. doi: 10.6113/JPE.2012.12.1.181

[2] P. Wlodarczyk, A. Sumper, and M. Cruz, "Voltage Control of Distribution Grids with Multi-Microgrids Using Reactive Power Management," Advances in Electrical and Computer Engineering, Vol. 15, No. 1, pp. 83-88, 2015. doi: 10.4316/AECE.2015.01012

[3] Z. Li, C. Zang, P. Zeng, H. Yu, H. Li, and S. Li, "Analysis of multi-agent-based adaptive droop-controlled AC microgrids with PSCAD: modeling and simulation," Journal of Power Electronics, Vol. 15, No. 2, pp. 455-468, March 2015. doi: 10.6113/JPE.2015.15.2.455

[4] B. Zhao, X. Zhang, J. Chen, C. Wang, and L. Guo, "Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system," IEEE Trans. on Sustainable Energy, Vol. 4, No. 4, pp. 934-943, Oct. 2013. doi: 10.1109/TSTE.2013.2248400

[5] W. Doorsamy, and W. A. Cronje, "State estimation on stand-alone DC microgrids through distributed intelligence", International Conference on Renewable Energy Research and Applications (ICRERA), pp. 227-231, November 2015. doi: 10.1109/ICRERA.2015.7418700

[6] N. Hatziargyriou, Microgrids: architectures and control. John Wiley and Sons Ltd, IEEE Press, 2014. doi: 10.1002/9781118720677

[7] IEEE Standards Association, IEEE guide for design, operation, and integration of distributed resource island systems with electric power systems. Institute of Electrical and Electronics Engineers (IEEE), IEEE 1547.4, 2011. doi: 10.1109/IEEESTD.2011.5960751

[8] K. Ubilla, G. A. Jiménez-Estévez, R. Hernádez, L. Reyes-Chamorro, C. H. Irigoyen, B. Severino, and Rodrigo Palma-Behnke, "Smart microgrids as a solution for rural electrification: Ensuring long-term sustainability through cadastre and business models," IEEE Transactions on Sustainable Energy, Vol. 5, No. 4, pp. 1310-1318, October 2014. doi: 10.1109/TSTE.2014.2315651

[9] S. Mashayekh, and K. L. Butler-Purry, "An integrated security-constrained model-based dynamic power management approach for isolated microgrids in all-electric ships", IEEE Transactions on Power Systems, Vol. 30, No. 6, pp. 2934-2945, Nov. 2015. doi: 10.1109/TPWRS.2014.2377741

[10] L. Guo, W. Liu, X. Li, Y. Liu, B. Jiao, W. Wang, C. Wang, and F. Li, "Energy management system for stand-alone wind-powered-desalination microgrid", IEEE Transactions on Smart Grid, Early access, Dec. 2014. doi: 10.1109/TSG.2014.2377374

[11] A. Kwasinski, "Quantitative evaluation of DC microgrids availability: Effects of system architecture and converter topology design choices", IEEE Transactions on Power Electronics, Vol. 26, No. 3, pp. 835-851, March 2011. doi: 10.1109/TPEL.2010.2102774

[12] T. Dragicevic, J. M. Guerrero, and J. C. Vasquez, "A distributed control strategy for coordination of an autonomous LVDC microgrid based on power-line signaling", IEEE Transactions on Industrial Electronics, Vol. 61, No. 7, pp. 3313-3326, July 2014. doi: 10.1109/TIE.2013.2282597

[13] G. R. Saridis, "Towards the realization of intelligent controls", Proceedings of the IEEE, Vol. 67, No. 8, pp. 1115-1133, August 1979. doi: 10.1109/PROC.1979.11407

[14] S. J. S. Tsai, and K. H. Wong, "On-line estimation of Thevenin equivalent with varying system states," IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, pp. 1-7, 2008. doi: 10.1109/PES.2008.4596364

[15] B. Brusilowicz, W. Rebizant, and J. Szafran, "Influence of the voltage regulation local stability margin of the receiving node", IEEE International Conference on Development in Power Systems Protection, Birmingham, pp. 1-6, Aril 2012. doi: 10.1049/cp.2012.0096

[16] X. Mou, W. Li, and Z. Li, "A preliminary study on the Thevenin equivalent impedance for power systems monitoring", IEEE International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, Shandong, pp. 730-733, July 2011. doi: 10.1109/DRPT.2011.5993988

[17] S. Haykin, A. Sayed, J. Zeidler, P. Yee, and P. Wei, "Adaptive tracking of linear time-variant systems by extended RLS algorithms," IEEE Transactions on Signal Processing, vol. 45, pp. 1118–1128, May 1997. doi: 10.1109/78.575687

[18] J. Mikleš, M. Fikar, Process modelling, identification and control. Springer, 2007. doi: 10.1007/978-3-540-71970-0

[19] G. W. K. Colman, and J. W. Wells, "On the use of RLS with covariance reset in tracking scenarios with discontinuities," IEEE Canadian Conference on Electrical and Computer Engineering, Ottawa, pp. 693-696, May 2006. doi: 10.1109/CCECE.2006.277663

[20] M. Ciobotaru, R. Teodorescu, P. Rodriguez, A. Timbus, and F. Blaajberg, "Online grid impedance estimation for single-phase grid-connected systems using PQ variations," IEEE Power Electronics Specialists Conference, Ottawa, pp. 2306-2312, June 2007. doi: 10.1109/PESC.2007.4342370

[21] G. Seo, C. B. Cho, and K. Lee, "DC islanding detection algorithm using injection current perturbation technique for photovoltaic converters in DC distribution," IEEE Energy Conversion Congress and Exposition, Raleigh, pp. 3722-3726, September 2012. doi: 10.1109/ECCE.2012.6342473

[22] Y. Bar-Cohen, Biomimetics: Biologically inspired technologies. CRC Press, 2005. doi: 10.1201/9781420037715

[23] C. Grosan, and A. Abraham, "Stigmergic optimization: Inspiration, technologies and perspectives," in Stigmergic Optimization, A. Abraham, C. Grosan, and R. Vitorino, Springer, 2006, pp. 1-24. doi: 10.1007/978-3-540-34690-6_1

[24] E. Bonabeau, M. Dorigo, and G. Theraulaz, "Inspiration for optimization from social insect behaviour," Nature, vol. 406, pp. 39-42, July 2000. doi: 10.1038/35017500

[25] H. V. D. Parunak, "A survey of environments and mechanisms for human-human stigmergy," in Environments for Multi-Agent Systems, D. Weyns, H. V. D. Parunak, and F. Michel, Springer, 2006, pp. 163-186. doi: 10.1007/11678809_10

[26] G. Hansson, and M. Uussalu, Analysis of the output impedance from switched DC/DC converters. Chalmers University of Technology, Master's Thesis, Gotenburg, Sweden, 2014.

[27] Y. Panov, and M. Jovanovic, "Practical issues of input/output impedance measurements in switching power supplies and application of measured data to stability analysis", IEEE Applied Power Electronics Conference and Exposition, vol. 2, pp. 1339-1345, 2015. doi: 10.1109/APEC.2005.1453183