Detection of Series DC Arc on a Distribution Node using Discrete-Time Parameter Identification Techniques

Kaushik K Gajula
Dept. of Electrical Engineering
University at Buffalo
Buffalo, NY 14260
Email: kaushikk@buffalo.edu

Luis Herrera
Dept. of Electrical Engineering
University at Buffalo
Buffalo, NY 14260
Email: lcherrer@buffalo.edu

Xiu Yao
Dept. of Electrical Engineering
University at Buffalo
Buffalo, NY 14260
Email: xiuyao@buffalo.edu

***Abstract*—Discrete-time parameter identification techniques are studied extensively and are implemented to detect and localize the series arc discharge on a multi-load distribution node. The techniques include Recursive Least Squares (RLS) and the Kalman Filter (KF) which by estimating the line parameters - resistance and inductance will help monitor their condition. The systems electrical components vary abruptly during an arc discharge on a line of the grid. This disturbance from the arc discharge also travels to the adjacent loads and lines. The RLS and KF will then act as detectors functioning on a line and consequently help localize the faulted line/load. The two mentioned techniques delineate the variation in values of the grid parameters even for a large noisy arc.**

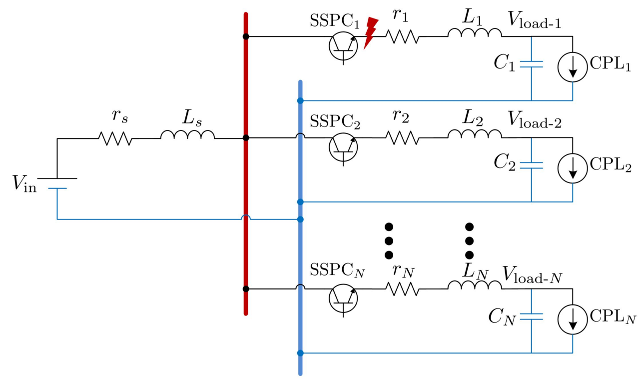


Fig. 1. Typical distribution node with N loads in parallel.

I. Introduction

Considering the increase in the use of dc based microgrids in areas such as the More Electric Aircraft (MEA), Electric Vehicles (EVs), power-grid etc, it has become highly essential to inhibit the hazards that occur during operation of dc circuits at high-voltages. One such fault that can cause a major risk to dc power systems is the series dc arc [1]. The dangers caused by the dc arc are mentioned in [2], [3] where it shows that extinguishing fire off an EV has a different approach to that of a gasoline car. Also in [4], there are multiple approaches shown to control fire that might occur in an EV. In [5], an F22 was also destroyed by an arc fault close to a hydraulic line.

Even though there are a variety of existing techniques available to detect series faults, few research has been conducted on its localization. It has been shown in [6]–[8], that the series arc noise signatures can travel to adjacent lines, possibly triggering detectors in multiple sections of the network. This paper uses the same experimental setup shown in [8]. A localization scheme for series and parallel ac arc faults has been proposed in [9], [10] using Fast Fourier Transform (FFT) and least squares. However, these methods require a large computation due to the need of computing the FFT of multiple signals at each time step. A similar approach for dc systems was studied in [11].

The discrete-time parameter estimation methods include the recursive least square algorithm and the Kalman Filter which are used in estimating the parameters of a dc-dc buck converter in [12]. The techniques used are adaptive in nature and [12] infers that the Kalman Filter is more robust and reliable in comparison to the recursive least square method by estimating with higher accuracy when an abrupt load change is applied to the buck converter. The theory, derivation and similarities of numerous discrete-time identification techniques are studied quite exquisitely in [13]. Lastly, in [14], a discrete-time model reference estimation using Auto Regressive Moving Average (ARMAX), was studied for the identification of ac faults.

In this paper, discrete-time parameter identification techniques are used to detect/localize series arc. Parameter identification techniques have recently been used for power electronics and PV monitoring applications [15]–[17]. The dc microgrid used in the paper is a linear circuit. A different identification technique can be used if the circuit is non-linear [13]. This paper is structured as follows. In Section II, a description of the dc network is presented. In Section III, a summary of the parameter identification techniques is discussed. Simulation results and experimental results are analyzed in Section IV and Section V respectively. Lastly, a conclusion and future work are stated.

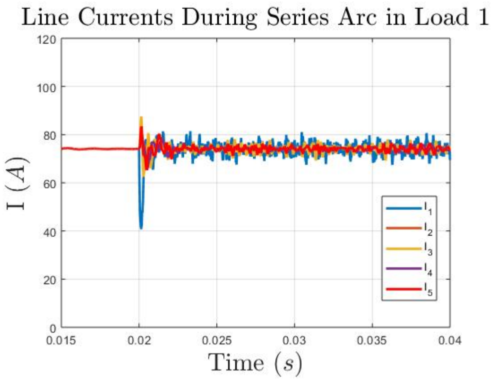


Fig. 2. Distribution node with 5 loads and series arc in load 1.

II. System Description

A simple distribution node of a typical dc microgrids is shown in Fig. 1. Each load constitutes of a dc voltage source, line inductance, line resistance, load capacitance, and an active load or Constant Power Load (CPL). Nowadays, there are Solid State Power Controllers (SSPCs) which are similar to a circuit breaker. The SSPCs analyze the input current and voltage transients to the loads and help in connecting/disconnecting loads if an overload occurs [18] thus protecting the load. These SSPCs are embedded with microprocessors using which advanced fault detection techniques can be implemented.

On occurrence of an arc discharge in a single or multiple lines, [6]–[8] reveal that the fault's noise affects the adjacent lines. The Fig. 2, displays a simulation of current flowing to five loads in a distribution node. It helps us understand that the noise from the fault that occurred on load one proliferates to all the lines commonly connected to the same voltage-source node. The current detection techniques would show faults on all the connected loads as they focus on the line current. In this section, two models will be presented to be used for parameter identification.

A. 1^{st} order system

In order to identify the line parameters, each line section can be modeled into a first order differential equation given by,

$$\frac{dI}{dt} = -\frac{r}{L}I + \frac{1}{L}\left[V_{in} - V_{out}\right] \tag{1}$$

where $r,\ L$ are the line resistance and line inductance respectively, I is the line current flowing through the inductor and the resistance, and $V_{\text{in}} - V_{\text{out}}$ defines the voltage across the line with V_{in} as the input voltage and V_{out} is the voltage at the output. We can convert the continuous-time differential equation shown in (1) to discrete-time equation by using Euler transformation where T is the time step. Equation (2) will be used to estimate the line parameters $r,\ L$.

$$I_{(k)} = \left[1 - \frac{r\,T}{L}\right] I_{(k-1)} + \frac{T}{L}\left[V_{in(k-1)} - V_{out(k-1)}\right] \tag{2}$$

The algorithms in the next section, require (2) to be placed in linear regression form given by,

$$y_{(k)} = H_{(k)}\, x_{(k)} + v_{(k)} \tag{3}$$

where $x_{(k)}$ contains the parameters to be estimated, $H_{(k)}$ is the basis matrix, $v_{(k)}$ is the measurement error and the $y_{(k)}$ is the measurement taken at the k^{th} time. We can relate the components of (2) to matrices of (3) as follows:

$$\left[V_{in(k-1)} - V_{out(k-1)}\right] = \frac{L}{T}\left[I_{(k)} - I_{(k-1)}\right] + r\, I_{(k-1)} \tag{4}$$

$$y_{(k)} = \left(V_{in(k-1)} - V_{out(k-1)}\right)$$

$$H_{(k)} = \begin{pmatrix} I_{(k)} - I_{(k-1)} & I_{(k-1)} \end{pmatrix}$$

$$x_{(k)} = \begin{pmatrix} \frac{L}{T}(k) \\ r(k) \end{pmatrix} \tag{5}$$

In state-space format,

$$x_{(k+1)} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \frac{L}{T}(k) \\ r(k) \end{pmatrix} + w_{(k)} \tag{6}$$

B. 2^{nd} order system

A second order system each load shown in Fig. 1 can be designed when it is desired to estimate the capacitance as well. This can be formulated in differential equations,

$$V_{in} = I_l r + L\frac{dI_l}{dt} + V_c \qquad C\frac{dV_c}{dt} = I_l - I_{load} \tag{7}$$

where, I_l denotes current through the inductor, V_c denotes voltage across the capacitor and I_{load} is the opposing current substituting for a large load.

Now, we can write (7) in continuous-time state-space:

$$\begin{pmatrix} \dot{I}_l \\ \dot{V}_c \end{pmatrix} = \begin{pmatrix} \frac{-r}{L} & \frac{-1}{L} \\ \frac{1}{C} & 0 \end{pmatrix} \begin{pmatrix} I_l \\ V_c \end{pmatrix} + \begin{pmatrix} \frac{1}{L} \\ 0 \end{pmatrix} V_{in} + \begin{pmatrix} 0 \\ \frac{-1}{C} \end{pmatrix} I_{load} \tag{8}$$

and use Euler transformation to convert the above continuous-time state-space to a discrete-time state-space:

$$\begin{pmatrix} I_{l(k)} \\ V_{c(k)} \end{pmatrix} = \begin{pmatrix} 1 - \frac{rT}{L} & \frac{-T}{L} \\ \frac{T}{C} & 1 \end{pmatrix} \begin{pmatrix} I_{l(k-1)} \\ V_{c(k-1)} \end{pmatrix} + \begin{pmatrix} \frac{T}{L} \\ 0 \end{pmatrix} V_{in(k-1)} + \begin{pmatrix} 0 \\ \frac{-T}{C} \end{pmatrix} I_{load(k-1)} \tag{9}$$

The above discrete-time state space needs to be further simplified in order to get it in a linear regression format.

As our focus is to estimate the r, L, C parameters of the grid inorder to detect the arc discharge we need to arrange to form the matrix equation as to contain the parameters in $x_{(k)}$ vector.

TABLE I. Summary of RLS and KF techniques

Recursive least square method	Kalman Filter
<u>Initialize:</u> $P_{(0)} = m\,\mathcal{P} \quad R = n\,\mathcal{R} \quad \lambda \in (0,1]$	<u>Initialize:</u> $P^{-}_{(0)} = m\,\mathcal{P} \quad R = n\,\mathcal{R} \quad Q = q\,\mathcal{Q}$
<u>Gain:</u> $K_{(k)} = P_{(k-1)}H^T_{(k)}[H_{(k)}P_{(k-1)}H^T_{(k)} + \lambda R]^{-1}$	<u>Gain:</u> $K_{(k)} = P^{-}_{(k)}H^T_{(k)}[H_{(k)}P^{-}_{(k)}H^T_{(k)} + R]^{-1}$
<u>Update:</u> $P_{(k)} = \frac{1}{\lambda}\,[P_{(k-1)} - K_{(k)}H_{(k)}P_{(k-1)}]$ $\hat{x}_{(k)} = \hat{x}_{(k-1)} + K_{(k)}[y_{(k)} - H_{(k)}\hat{x}_{(k-1)}]$	<u>Update:</u> $P^{+}_{(k)} = P^{-}_{(k)} - K_{(k)}H_{(k)}P^{-}_{(k)}$ $\hat{x}^{+}_{(k)} = \hat{x}^{-}_{(k)} + K_{(k)}[y_{(k)} - H_{(k)}\hat{x}^{-}_{(k)}]$
	<u>Propagation:</u> $P^{-}_{(k)} = F_{(k-1)}P^{+}_{(k-1)}F^T_{(k-1)} + Q_{(k-1)}$ $\hat{x}^{-}_{(k)} = F_{(k-1)}\hat{x}^{+}_{(k-1)} + G_{(k-1)}u_{(k-1)}$

This would form the linear regression equation shown in (3) as follows:

$$y_{(k)} = \begin{pmatrix} I_{l(k)} - I_{l(k-1)} \\ V_{c(k)} - V_{c(k-1)} \end{pmatrix}$$

$$H_{(k)} = \begin{pmatrix} I_{l(k-1)} & V_{in(k-1)} - V_{c(k-1)} & 0 \\ 0 & 0 & I_{l(k-1)} - I_{load(k-1)} \end{pmatrix}$$

$$x_{(k)} = \begin{pmatrix} \dfrac{-\,rT_s}{L}(k) \\ \dfrac{T_s}{L}(k) \\ \dfrac{T_s}{C}(k) \end{pmatrix} \tag{10}$$

In state-space format,

$$x_{(k+1)} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \dfrac{-\,rT_s}{L}(k) \\ \dfrac{T_s}{L}(k) \\ \dfrac{T_s}{C}(k) \end{pmatrix} + w_{(k)} \tag{11}$$

III. Parameter Identification Techniques

As the system can be written in the form of the equation shown in (3), the goal of the identification techniques is to estimate the system's parameters stored in the vector x by using the measurements obtained y and the matrix H. In addition, identifying these parameters can help us detect a change in their values, which would denote an occurrence of an unprecedented event. In our case the techniques would help detect the dc-arc.

A. Recursive Least Squares (RLS)

The RLS method starts by defining the covariance matrices:

$$R_{(k)} = E(v_{(k)}v^T_{(k)})$$
$$P_{(k)} = E[(\hat{x}_{(k)} - x)(\hat{x}_{(k)} - x)^T]$$

where $R_{(k)}$ denotes the measurement error covariance matrix and $P_{(k)}$ denotes the error covariance matrix related to the $x_{(k)}$. $\hat{x}_{(k)}$ is the estimate of x at k^{th} interval. $P_{(k)}$ and $R_{(k)}$ are initialized as follows:

$$P_{(0)} = m\,\mathcal{P} \quad R = n\,\mathcal{R} \tag{12}$$

where, m, n are positive integers. $\mathcal{P}$ and $\mathcal{R}$ are generally identity matrices unless correlation exists.
The gain is calculated at every iteration by,

$$K_{(k)} = P_{(k-1)}H^T_{(k)}[H_{(k)}P_{(k-1)}H^T_{(k)} + \lambda R]^{-1}$$

and the update phase of the RLS algorithm consists of the following steps:

$$P_{(k)} = \frac{1}{\lambda}\,[P_{(k-1)} - K_{(k)}H_{(k)}P_{(k-1)}]$$
$$\hat{x}_{(k)} = \hat{x}_{(k-1)} + K_{(k)}[y_{(k)} - H_{(k)}\hat{x}_{(k-1)}]$$

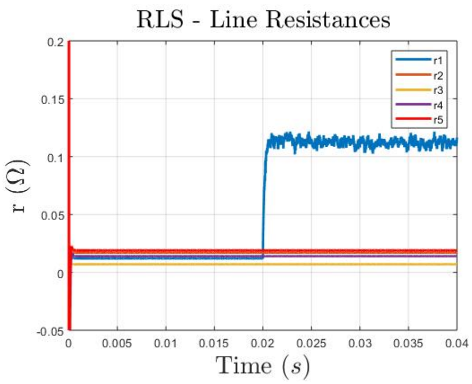
where λ is the forgetting factor which takes a value $\in (0,1]$ and $K_{(k)}$ is the gain matrix.

B. Kalman Filter (KF)

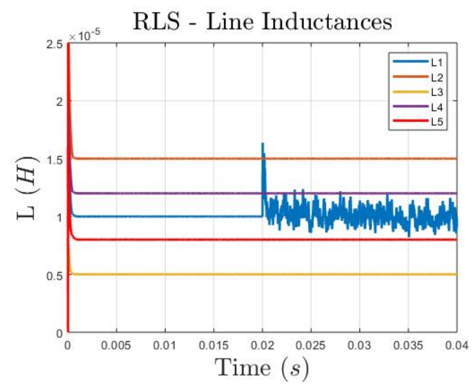
The Kalman Filter has, considerable number of similarites to the RLS. Its higher efficiency to the RLS is because of its formulation of the vector x as a state. This can be shown by,

$$x_{(k)} = F_{(k-1)}x_{(k-1)} + G_{(k-1)}u_{(k-1)} + w_{(k-1)}$$

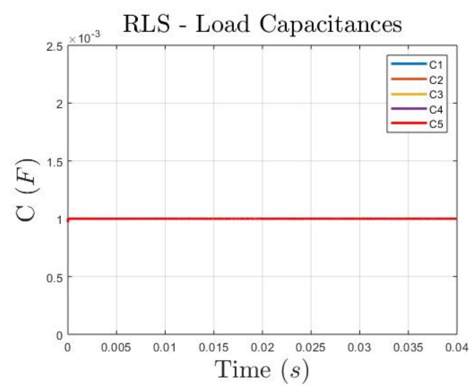
The above state space for the 1^{st} order system is shown in (6) and for the 2^{nd} order system is shown in (11). Here, $w_{(k-1)}$ is called the process noise. The process covariance matrix is hence defined as $Q_{(k)}$, which is given by $Q_{(k)} = E(w_{(k)}w^T_{(k)})$. $Q_{(k)}$ can be initialized as $Q = q\,\mathcal{Q}$ in addition to $P_{(0)}$ and R



(a) Tracking of line resistances

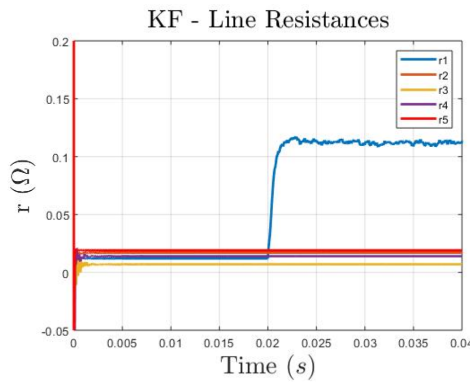


(b) Tracking of line inductances

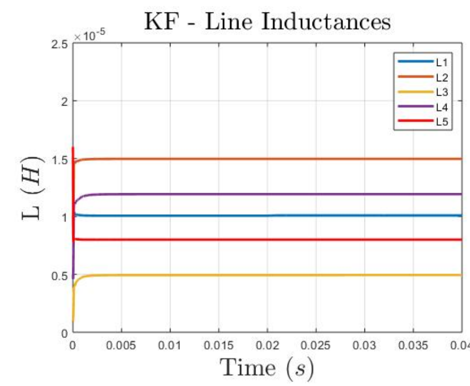


(c) Tracking of capacitances

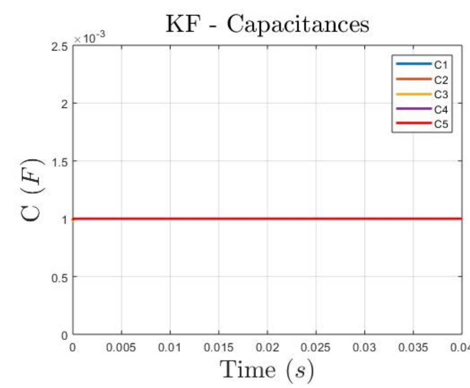
Fig. 3. Simulation results of a distribution node with five loads using Recursive Least Squares when, series arc occurs at $t = 0.02$ s in load 1 only.



(a) Tracking of line resistances



(b) Tracking of line inductances



(c) Tracking of capacitances

Fig. 4. Simulation results of a distribution node with five loads using Kalman Filter when, series arc occurs at $t = 0.02$ s in load 1 only.

which are shown in (12). Notice, that we can fix a constant value for R and Q unlike P.
The gain of the Kalman Filter is given by,

$$K_{(k)} = P^-_{(k)} H^T_{(k)} [\, H_{(k)} P^-_{(k)} H^T_{(k)} + R \,]^{-1}$$

the propagation phase of the Kalman Filter are given by,

$$P^-_{(k)} = F_{(k-1)} P^+_{(k-1)} F^T_{(k-1)} + Q_{(k-1)}$$
$$\hat{x}^-_{(k)} = F_{(k-1)} \hat{x}^+_{(k-1)} + G_{(k-1)} u_{(k-1)}$$

and the update phase for the Kalman Filter are given by,

$$\hat{x}^+_{(k)} = \hat{x}^-_{(k)} + K_{(k)} [y_{(k)} - H_{(k)} \hat{x}^-_{(k)}]$$
$$P^+_{(k)} = P^-_{(k)} - K_{(k)} H_{(k)} P^-_{(k)}$$

IV. Simulation Results

The grid shown in Fig. 1 was simulated with the values of the electrical components shown in the Table II, the dc microgird model being used for the simulation is a 2^{nd} order

TABLE II. Simulation Parameters for Distribution Node with Five Loads

Load Number	Line r (Ω)	Line L (μH)	Load C (F)
Load 1	0.010	10	0.001
Load 2	0.015	15	0.001
Load 3	0.005	5	0.001
Load 4	0.012	12	0.001
Load 5	0.017	8	0.001

system with five loads. Each of the resistance, inductance, capacitance and load combination making a line section is tracked by their respective RLS or KF algorithms. The motive of the RLS and KF techniques is to track the values of line resistances, line inductances and load capacitances and eventually help localize the series dc arc faults with high noise. The inputs fed to the microgrid was $270 + 5sin(40000\,\pi t)$. Notice, that the input voltage consists of an ac frequency as it can be naturally generated by the switching of power electronics. The fault noise is implemented by a controlled current source driven by a random number generator with a variance of $1e5$.

The RLS and KF techniques for each of the line sections with their respective loads were formulated in MATLAB on the basis of the Table I with the second order model.

The series arc was set to occur at $0.02\,s$ on the line connected to $load$ 1. Fig 2 shows the repercussions of the series arc discharge in the form of a noise. The figure shows that an arc discharge affects all of the loads connected in parallel to the common voltage source node.

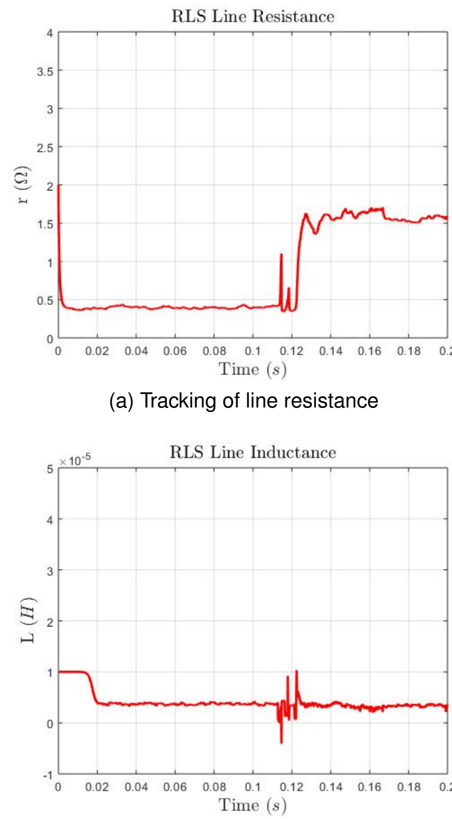
The results of the tracking of line parameters by RLS method are shown in Fig 3 and tracking by the KF technique are shown in Fig 4. As the series arc was set to occur at $0.02\ s$ the tracking results by both the methods depict the same i.e. the line resistance connected to the $load\,1$ shows a significant increase in its resistance value which indicates the occurrence of series high impedance arc fault.

V. Experimental Results

The experiment setup shown in Fig.7 was conducted using a single CPL which was approximated using a buck converter controlled by an Opal RT system [19]. The dc power supply was fed by Keysight N8929A [20]. The series high impedance arc was generated using, two copper rods which can be separated by a fixed speed to a set distance apart. The hardware setup for the experiment is shown in the paper [8].

The Figs. 5 and. 6 by RLS and KF respectively shows the estimation of line resistance and also detects the series arc by showing an increase in value of the same as an outcome of the high impedance of the fault. It should be noted that the inductance can be estimated accurately by using richer input, i.e. one more frequency.

The input voltage was set at $290\,V$ and the CPL was set to approximately $15\ A$. Series arc was set to occur at around $0.12\ s$. The first few samples taken during the arc discharge



(a) Tracking of line resistance

(b) Tracking of line inductance

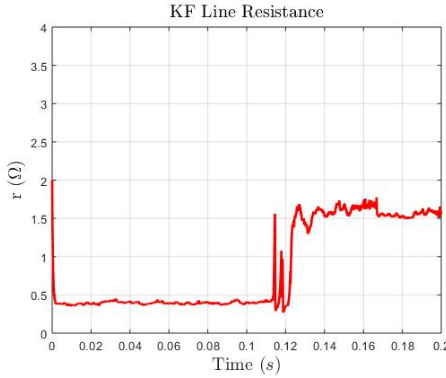
Fig. 5. Experimental results using Recursive Least Squares when, series arc occurs.

shows it to be random, but eventually it leads into a sustained arc which is traced by a constant high impedance value in the plot showing line resistance estimation in both the techniques.

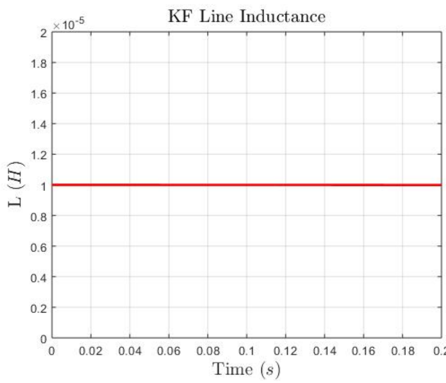
VI. Conclusion And Future Work

Parameter identification techniques in discrete-time were studied and were evaluated in order to detect and localize series dc arc within a faulted line/load. In particular, RLS and KF were implemented both in simulation and experimental results to estimate the line resistance and line inductance. It was shown that these methods are effective in detecting series arc by properly estimating the line resistance and its change during series arc, even in the presence of noise generated by it. The simulation results obtained from the microgrid with 5 loads shows localizing of the fault line and to avoid it from tripping off multiple loads since the disturbance spreads to all of its adjacent loads.

In future, multiple CPLs will be set in parallel to test the identification techniques shown in this paper as well as in [8]. Also, a microgrid consisting of non-linear electrical components will be simulated/tested upon using suitable algorithms. This would help bring forward applications of localizing a crtical arc discharge in electrical equipments.



(a) Tracking of line resistance



(b) Tracking of line inductance

Fig. 6. Experimental results using Kalman Filter when, series arc occurs.

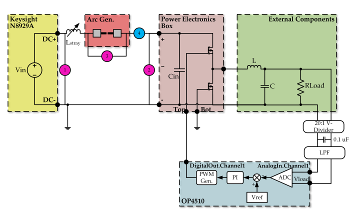


Fig. 7. Experimental setup for series dc arc with active loads.

References

[1] X. Yao, L. Herrera, S. Ji, K. Zou, and J. Wang, "Characteristic study and time-domain discrete- wavelet-transform based hybrid detection of series dc arc faults," *IEEE Transactions on Power Electronics*, vol. 29, no. 6, pp. 3103–3115, June 2014.

[2] D. Tracy. Here's what firefighters do to extinguish a battery fire on a tesla model s. Available at https://jalopnik.com/watch-volunteer-firefighters-in-austria-extinguish-a-fi-1819665352.

[3] Fire chief: Tesla crash shows electric car fires could strain department resources. Available atl http://abc7news.com/automotive/fire-chief-tesla-crash-shows-electric-car-fires-could-strain-department-resources/3266061/.

[4] Tesla roadster emergency responder guide. Available at l https://www.tesla.com/firstresponders.

[5] F22 raptor news by air combat command, 2012. Available at http://www.f-16.net/f-22-news-article4773.html.

[6] X. Yao, L. Herrera, and J. Wang, "Impact evaluation of series dc arc faults in dc microgrids," in *2015 IEEE Applied Power Electronics Conference and Exposition (APEC)*, March 2015, pp. 2953–2958.

[7] X. Yao, "Study on dc arc faults in ring-bus dc microgrids with constant power loads," in *2016 IEEE Energy Conversion Congress and Exposition (ECCE)*, Sept 2016, pp. 1–5.

[8] L. Herrera and X. Yao, "A parameter identification approach to series dc arc fault detection and localization," in *2018 IEEE Energy Conversion Congress and Exposition (ECCE)*, Sept 2018, pp. 1–5.

[9] A. Yaramasu, Y. Cao, G. Liu, and B. Wu, "Intermittent wiring fault detection and diagnosis for sspc based aircraft power distribution system," in *2012 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, July 2012, pp. 1117–1122.

[10] ——, "Aircraft electric system intermittent arc fault detection and location," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 51, no. 1, pp. 40–51, January 2015.

[11] E. Christopher, M. Sumner, D. W. P. Thomas, X. Wang, and F. de Wildt, "Fault location in a zonal dc marine power system using active impedance estimation," *IEEE Transactions on Industry Applications*, vol. 49, no. 2, pp. 860–865, March 2013.

[12] M. Ahmeid, M. Armstrong, S. Gadoue, M. Al-Greer, and P. Missailidis, "Real-time parameter estimation of dc x2013;dc converters using a self-tuned kalman filter," *IEEE Transactions on Power Electronics*, vol. 32, no. 7, pp. 5666–5674, July 2017.

[13] J. L.Crassidis and J. L.Junkins, *Optimal Estimation of Dynamic Systems*. CRC Press, 2012, [ISBN :978-1-4398-3985-0].

[14] J. B. Beck and D. C. Nemir, "Arc fault detection through model reference estimation," SAE Technical Paper, Tech. Rep., 2006.

[15] J. Poon, P. Jain, C. Spanos, S. K. Panda, and S. R. Sanders, "Fault prognosis for power electronics systems using adaptive parameter identification," *IEEE Transactions on Industry Applications*, vol. 53, no. 3, pp. 2862–2870, May 2017.

[16] ——, "Photovoltaic condition monitoring using real-time adaptive parameter identification," in *2017 IEEE Energy Conversion Congress and Exposition (ECCE)*, Oct 2017, pp. 1119–1124.

[17] P. Jain, J. Poon, L. Jian, C. Spanos, S. R. Sanders, J. X. Xu, and S. K. Panda, "An improved robust adaptive parameter identifier for dc-dc converters using h-infinity design," in *2018 IEEE Applied Power Electronics Conference and Exposition (APEC)*, March 2018, pp. 2922–2926.

[18] T. R. Maher, N. E. LeComte, and K. W. Kawate, "Solid state power controller," Mar. 1998.

[19] "Opal RT," https://www.opal-rt.com/.

[20] "Keysight," https://www.keysight.com/us/en/home.html.