Accurate Line Resistance Estimation in a Multi-source Electrical Power System of the More Electric Aircraft: An Intelligent and Data-Driven Approach

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***Abstract*—Knowledge of the line resistance is very important in the analysis of the electrical power systems (EPS) and their control operations. Some of the existing line resistance estimation methods require the utilization of many devices, involve the injections of disturbances to the systems and are computationally intensive. Hence, the processes take longer times to accomplish, have the possibility of making errors, could affect the power quality and inquire additional costs for the system. Surrogate modelling is an excellent alternative to ease the burden associated with complex computation, save cost and increase the reliability of the system. In this paper, an artificial neural network (ANN)-based surrogate model is proposed for the estimation of line resistance in the DC grid of the more electric aircraft (MEA) electrical power system (EPS). A neural network (NN) model is employed and trained based on a set of data obtained from multiple simulations to serve as a dedicated surrogate model of the detailed MEA EPS simulation model. The surrogate model is trained to establish the relationship between the output current of the converters to the corresponding line resistance within the design space with high accuracy. Thereafter, for every change in the line resistance between the parallel-connected converters and the DC bus in the MEA EPS, the output current of the converter can be provided as input to the surrogate model to predict the corresponding line resistance. The results obtained show that the surrogate model can accurately estimate the line resistance with an error of less than 1% provided the line resistance is within the design space used in training it.**

Keywords—Line resistance estimation, neural network, more electric aircraft, surrogate modelling, droop control

I. Introduction

The aviation industry is making concerted efforts to decrease the pollution level in the atmosphere by moving toward more electric aircraft (MEA). The MEA concept is a major trend in the modern aircraft industry for the development of aircraft that are fuel-efficient. This will ultimately lead to a reduction in gas emission, fuel consumption, maintenance and cost of operation [1]. In the MEA, the conventional secondary sources of power for the aircraft such as the pneumatic, mechanical actuators, and hydraulic will be replaced by the electrical power. As a result, there is a huge increase in the electrical loads onboard the aircraft, and this leads to significant demand for electrical power by the loads. Hence, it is paramount to extract electric power from both the high-pressure (HP) and low-pressure (LP) engine shafts. As shown in Fig.1, the HP and LP shafts that are situated within the engine of the aircraft are each driving a generator and feeding power to a single DC bus via a power converter.

The droop control method is normally employed for load current sharing among multiple sources. However, the conventional droop control method has limitations in realizing

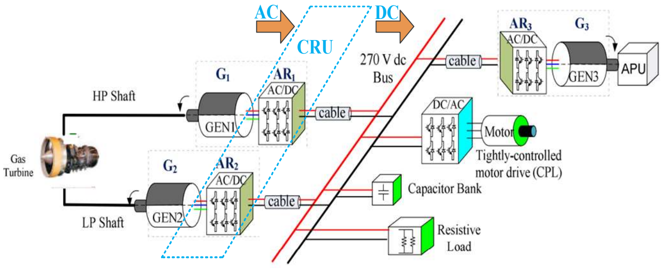


Fig. 1. Typical Multi-source Single DC Bus configuration for Future MEA EPS [4]

accurate current sharing among the multiple parallel-connected power converters and DC bus voltage regulation due to the influence of the mismatched line resistance and nominal voltage reference offset [2]. Thus, the knowledge of the line resistance can be utilized to adjust the droop parameters to achieve accurate current sharing and good voltage regulation [3].

In most of the existing methods, the line impedance is estimated using many hardware measurement devices. However, the use of many hardware resources makes such existing line resistance estimation methods prone to errors, time-consuming and costly [4, 5]. Also, the injection of current harmonics into the grid and then measuring the corresponding voltage and current is one of the common techniques employed in estimating the line resistance [6, 7]. However, the injection of disturbance into the grid could potentially affect the power quality of the electrical power system [8]. In [6, 3], the line resistance information is used to compensate for the droop coefficient to achieve enhanced current sharing among the multiple sources in the grid and to realize good voltage regulation.

In practical terms, the line resistance is unavoidable, unknown and cannot be controlled. However, the line resistance is usually a function of the conducted current and the cable length [9]. Furthermore, the line resistance may not be constant during the electrical power system (EPS) operation and could vary with changes in environmental conditions [10]. Therefore, there is a need to find a cost-effective way to estimate the line resistance in the DC microgrid. The estimation of line resistance using mathematical calculation is proposed in [3]. However, the proposed method still requires the measurement of the bus voltage and the converter's output currents.

Artificial neural networks have been widely employed in the field of power electronics research for parameters estimations as can be seen in [11, 12]. The resistance of the cable linking the parallel-connected converters to the DC bus in the DC grid of the MEA EPS is estimated with the aid of an artificial neural network in [5]. Furthermore, they have been employed to find the solution to diverse and difficult problems such as the identification and control of nonlinear systems and load power forecasting by training the NN model in a supervised way. The surrogate model can make predictions effectively without running the original system it is required to emulate. To this end, the surrogate model is developed by a supervised learning algorithm until when it can be used to replace the original system to perform a task [13].

The method proposed in this paper is hinged on the fact that for every change in the resistance of the lines connecting the parallel-connected converters to the DC bus bar shown in Fig. 1, the output currents of the converters will also change. Based on this premise, this paper proposes an intelligent and data-driven approach for the estimation of line resistance in the DC microgrid of the MEA EPS in an accurate and fast manner. In the proposed method, the output currents of the converters which are usually measured to control the converter are recorded for every combination of the line resistance within a design space. Thereafter, a surrogate model is trained to effectively map the output currents of the converters to the corresponding line resistance. When compared to the existing approaches used in the estimation of line resistance, the proposed method will save cost and enhance the EPS reliability. This is because the output current of the converter is the only parameter that is required to be known. Moreover, the knowledge of this parameter is essential in the normal control operation of the microgrid.

The rest of the paper is organized as follows. In section II the system description and its control model are discussed. Section III presents the proposed NN-based surrogate model approach in the estimation of line resistance. The validation of the proposed approach is provided in Section IV using simulation studies. Section V concludes the paper.

II. System Description and Basic Analysis of the Droop Control Method

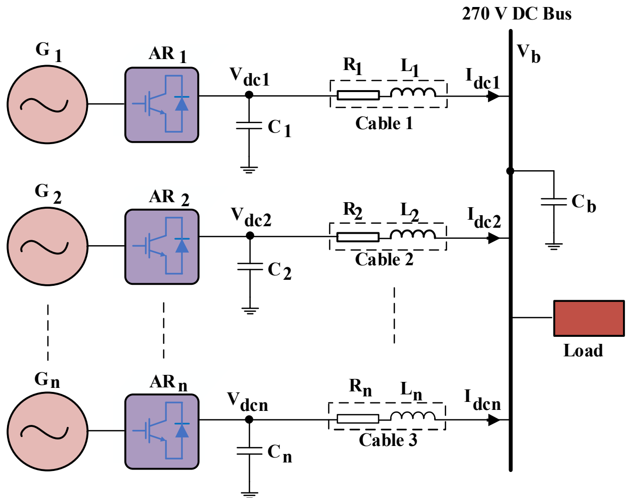


Fig. 2. DC grid Architecture for Future MEA EPS with Multiple Generators

A. Brief Description of the System under Study

The MEA EPS under study in this paper is an islanded DC microgrid that is made up of multiple sources (i.e. permanent magnet synchronous generators (PMSGs)), power converters, capacitor bank and loads as shown in Fig. 2. The sources are connected in parallel and supply power to a common DC bus. The power converters which are interfaced to the variable frequency generators are active front end controlled rectifiers (AR). They are used for the control and regulation of the output voltage of the sources they are interfaced with using the pulse-width modulation technique. C_1-C_n and C_b represent the local and main capacitor banks respectively. The load is usually comprised of resistive and constant power loads (CPL).

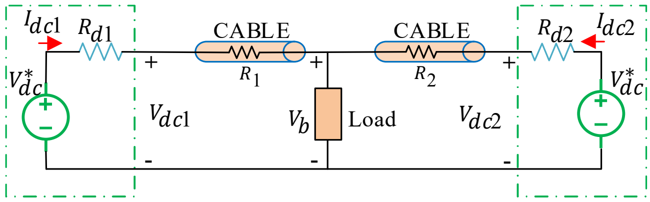


Fig. 3. Steady-state Equivalent Circuit of the Distribution Network

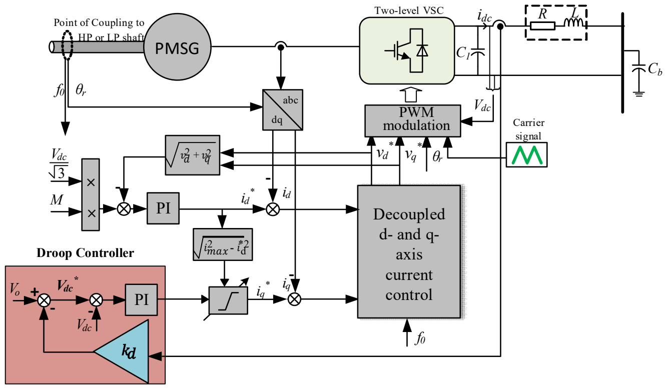


Fig. 4. Voltage-mode droop control scheme of a generator source fed by an active rectifier (AR) in the studied MEA EPS.

B. Analysis of the Basic Droop Control Concept

The basic MEA system with two sources is considered first in this paper. This will provide a general solution, with more than two sources to be considered in the future study. For ease of analysis, the generators *($G_{1\text{-}3}$)* with their interfacing parallel-connected converters shown in Fig. 2 can be modelled as an ideal voltage source under the droop control as shown in Fig. 3. Similarly, for steady-state analysis, the cable can be modelled as resistance. With only two sources considered, the equivalent circuit of the MEA EPS distribution network is shown in Fig. 3. A more detailed analysis of the droop control method as related to the DC microgrid can be found in [2].

If the voltage drop on the lines is not ignored and the voltage control dynamics are not put into consideration, the DC bus voltage as obtained from Fig. 3 in steady-state is expressed in (1). It can be observed from (1) that due to the droop action and coupled with the voltage drop across the line resistance, the DC bus voltage regulation becomes deteriorated.

$$V_b = V_{dci} - R_i I_{dci} = V_0 - (R_{di} + R_i) I_{dci} \tag{1}$$

where i = 1,2 represents the converter 1 and 2 respectively, V_{dc}^* is the common nominal voltage reference for each of the DC sources under no-load conditions, V_{dci} is the output terminal voltage of the i^{th} DC source, R_{di} is the equivalent output resistance (or droop resistance) of the i^{th} DC source, and I_{dci} is the output current from the i^{th} DC source, R_i is the resistance of the lines connecting the i^{th} DC source to the load and V_b is the main DC bus voltage. Under the no-load condition, $V_{dc1}{}^* = V_{dc2}{}^* = V_0$. Therefore, from (1), the current sharing ratio between the sources is as expressed in (2), assuming the sources are supplying together.

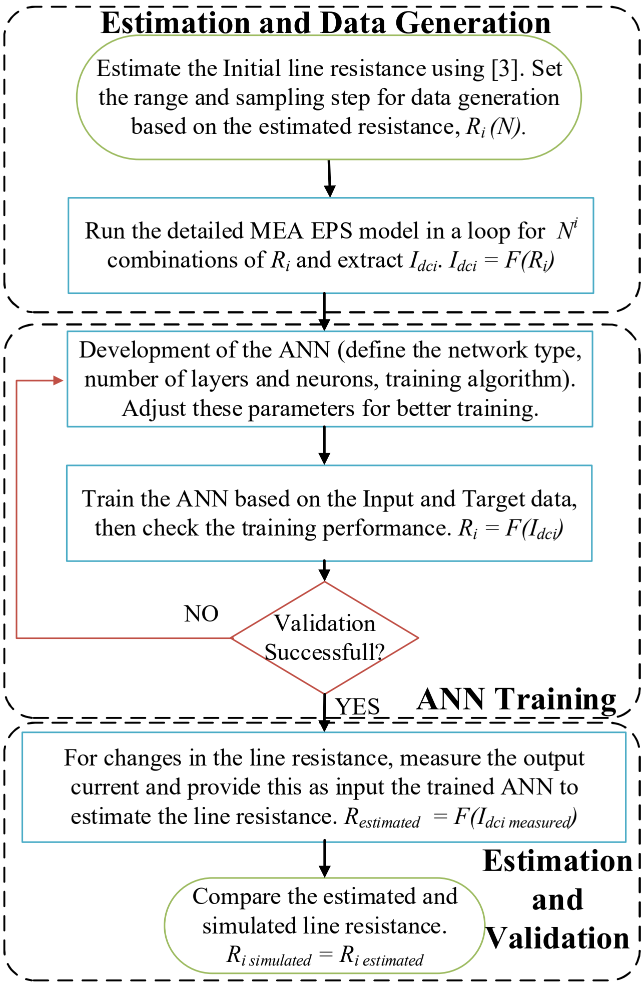
$$I_{dc} : I_{dc2} = \frac{1}{k_{d1}+R_1} : \frac{1}{k_{d2}+R_2} \tag{2}$$

where $k_{d1}=R_{d1}$ and $k_{d2}=R_{d2}$ are the droop gains of each of the converters.

It can be observed from (2) that the current sharing ratio of the sources will be influenced by both the line resistance and droop coefficient. Hence, the accuracy of the output current sharing among the converter may not be as desired because of the unequal voltage drop across the mismatched line resistance. To achieve accurate current sharing and suppress the circulating current in the DC microgrids, the authors in [3] proposed the estimation of the line resistance to adjust the droop coefficient using the expression in (3).

$$R_i = \frac{V_{dc}^* - V_b}{I_{dci}} - k_{di} \tag{3}$$

It can be seen from (3) that by measuring the DC bus voltage, the output current of the converters and knowing the droop coefficient of the converters, the line resistance can be estimated. This implies that, for every change in the line resistance, the DC bus voltage and output current of the converter is required to be measured to estimate the line



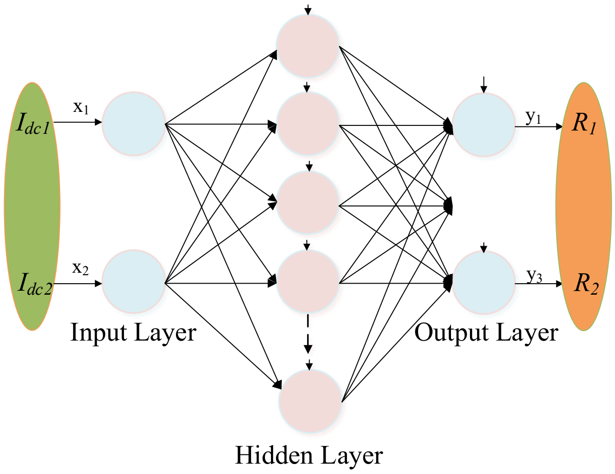


Fig. 6. Structure of the three-layer FFNN which serves as a surrogate model of the MEA EPS Control model shown in Fig. 4.

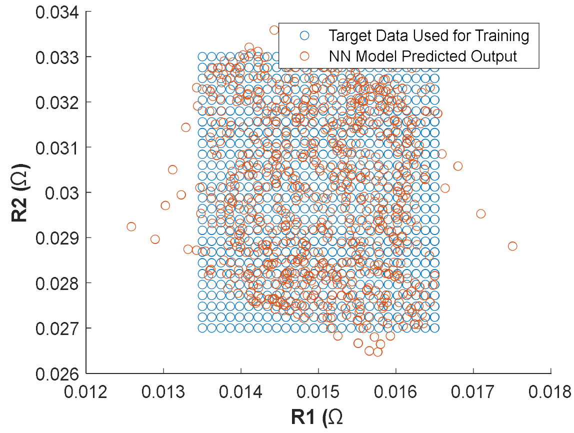


Fig. 7. Comparison between Predicted Output of the Surrogate Model and Target Data used for Training

resistance. Thus, an approach that is data-driven and intelligent and that only requires the measurement of the output current of the converter is proposed in this paper. However, the method proposed in [3] will be used in this paper to estimate the initial line resistance and for data generation.

III. Proposed Line Resistance Estimation Approach

Fig. 4 shows the detailed MEA EPS control model and will be used as the case study of the proposed line resistance estimation method. The power converter shown in Fig. 4 and interfaced to the PMSG is controlled using the voltage-mode droop control scheme. Only one source is shown in Fig. 4 to conserve space. The NN-based surrogate model can be well trained after obtaining the datasets. This can be achieved by exploring all the combinations of the line resistance in the design space.

A. Methodology

There are three stages involved in the proposed intelligent and data-driven based line resistance estimation method. A flowchart of the proposed line resistance estimation method is shown in Fig. 5. In the first stage, for every combination of the line resistance (R_1 and R_2) within the design space, a detailed simulation model of the MEA EPS is run in a loop and the corresponding output DC currents of the converters (I_{dc1} and I_{dc2}) are recorded. It is important to also mention that, the line resistance combinations are used as input to the detailed MEA

EPS simulation model in this stage. The droop coefficients of the converters are kept constant as is the case with the traditional droop control method.

In the second stage, the NN is trained to serve as a surrogate model of the system under the case study using the data generated from stage one. The NN-based surrogate model is trained offline with the recorded output currents of the converters as input and the line resistance as output. In the third and final step, for every change in the line resistance, the output current of the converters will be provided to the trained NN model to estimate the corresponding line resistance very fast and accurately. The data generation and training of the NN stages are required to be executed once for the detailed system model parameters.

B. *Data generation*

The detailed MEA EPS system control model shown in Fig. 4 was developed using the MATLAB SIMULINK©. A constant power load (CPL) of 40 kW was applied to the MEA EPS for the data generation. The system parameters and the initially estimated equivalent DC line resistance are as shown in TABLE I and TABLE II respectively.

For the proposed method, the line resistance design space is defined based on the initial estimated line resistance shown in TABLE II. A range of $\pm 10\%$ of the initial estimated line resistance is used for data generation and to accommodate any error in the initial estimation of the line resistance. However, the EPS designer can decide the percentage of the initial estimated cable resistance to be used as the design space. The design space and sampling step of the line resistance (R_1 and R_2) used for data generation are shown in TABLE III. As shown in TABLE III, 26 settings for each of the line resistances were tested, thus, making a total of $26^2 = 676$ combinations of the line resistance. The NN model is then trained and evaluated with 676 sets of data.

TABLE I. ELECTRICAL POWER SYSTEM PARAMETERS

Parameter	Symbol	Value
Rated Voltage of DC Bus	V^0	270 V
Local Shunt Capacitor	C_i	1.2 mF
Main DC bus capacitor	C_b	0.6 mF
Droop Coefficient of Converters	k_{d1}	1/4.250
	k_{d2}	1/4.250

TABLE II. INITIAL ESTIMATED LINE PARAMETERS

	Resistance (R_i)-(0.6 mΩ/m)	Inductance (L_i) - (0.2 µH /m)	Length (m)
Cable 1	15 mΩ	5 µH	25
Cable 2	30 mΩ	10 µH	50

TABLE III. DESIGN SPACE

Paramter	Range (mΩ)	Step (mΩ)	Samples
R_1	[13.5 16.5]	0.12	26 x 26= 676
R_2	[27 33]	0.24	

C. *ANN Structure and Training*

In this paper, the Feed-forward neural network (FFNN) structure is preferred to train the NN model. The FFNN is chosen because of the static relationship between the output current of the converters and line resistances [5]. The structure of the FFNN model used in this paper is shown in Fig. 6. It is made up of an input layer with 2 neurons, a hidden layer with 6 neurons and an output layer with 2 neurons. The 2 neurons in the input layer represent the two output DC current of the converters (I_{dc1} and I_{dc2}), while the two-line resistances (R_1 and R_2) are represented by the 2 neurons in the output layer of the FFNN. The training was carried out using the Levenberg-Marquardt backpropagation technique to optimize the weights and bias of the NN model. This is implemented by the NN fitting toolbox in MATLAB.

The 676 data sets are divided into three: 70% were used for training, 15% for validating the training, and the other 15% were used to test the performance of the trained NN model. The root mean square error (RMSE) was used to validate the training performance of the NN-based surrogate model. The closer the value of the RMSE between the output of the trained NN model and the targeted data used in training to zero, the better the training of the surrogate model. The calculated RMSE are 0.0003696 (Ω) and 0.00037953(Ω) for R_1 and R_2 respectively. Hence, it can be concluded that the surrogate model is well trained. The comparison between the NN model prediction and the target data used for training is shown in Fig. 7.

IV. SIMULATION RESULTS

To validate the proposed approach, a simulation study was conducted. The electrical power system parameters used for the simulation are the same as those shown in TABLE I. A CPL of 40 kW was applied during the simulation just as the case in data generation.

To assess the accuracy of the trained NN-based surrogate model in estimating the line resistance, a set of randomly selected line resistance values are used in the detailed simulation model of the MEA EPS model and the output current of the converter is recorded. The recorded output current of the converter is then used as input for the trained NN model. TABLE IV shows the recorded changes in the output currents of the converters as the randomly selected line resistance are simulated.

TABLE IV. RECORDED OUTPUT CURRENT FOR DIFFERENT RANDOMLY SELECTED LINE RESISTANCE

Cases (n)	Simulated R_i (mΩ)		Output DC Current (A)	
	R_1	R_2	I_{dc1}	I_{dc2}
1	14.0	28.0	82.33	77.97
2	16.0	28.5	82.16	78.26
3	16.4	29.5	82.27	78.19
4	15.0	30.0	82.56	77.86
5	15.5	30.5	82.54	77.91
6	15.8	31.4	82.65	77.83
7	16.2	31.6	82.63	77.88
8	15.0	32.5	82.95	77.53

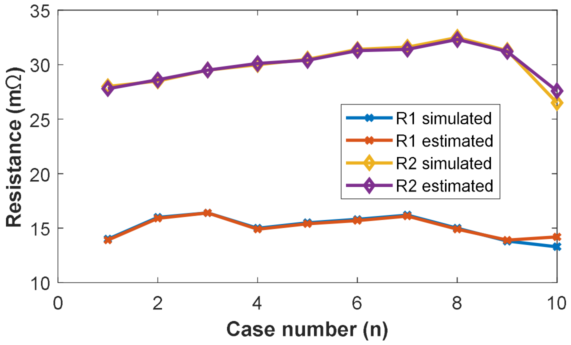


Fig. 8. Comparison between simulated line resistance and surrogate model estimated line resistance

9	13.8	31.3	82.94	77.49
10	13.3	26.5	82.22	78.07

It can be observed from Fig. 8 that the simulated and estimated cable resistance matched excellently well for changes in the line resistance that are within the design space. However, when the change in line resistance is not within the design space (as in case 10), the estimation capability of the trained NN model is poor for obvious reasons. Despite the small changes in the output current of the converters as shown in TABLE IV, the trained neural network can effectively estimate the corresponding line resistance.

V. Conclusion

This paper presents a neural network-based surrogate model that can be used as a tool for the fast and accurate estimation of line resistance in the DC microgrid of the MEA EPS. The only parameter that needs to be known is the output current of the converter, hence, this will reduce the number of resources required for measurement, save cost and enhance the system reliability. Based on the results obtained, both the simulated and estimated line resistance matched excellently well.

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