Realising Duality Principle for Prognostic Models

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***Abstract*— The lack of scientific approaches in estimating the remaining useful life (RUL) of various components and devices used in complicated systems, such as airplanes remain to be addressed. Regardless, there has been some progress in demonstrating feasible and viable techniques so far that are relevant to 'integrated system health management' (ISHM). ISHM entails a series of techniques and scientific measures that have collaborative self-awareness features to increase the overall reliability of systems. However, these resulting systems were often too expensive and time consuming, as well as requiring a lot of resources to develop. This paper presents a radically novel approach for building prognostic models that compensates and improves on the inconsistencies and problems witnessed in current prognostic models. Essentially, it proposes a state of the art technique that utilizes the physics of a system rather than the physics of a component. An advantage to this approach is; the prognostic model can be generalized such that a new system could be developed on the basis and principles of the prognostic model of another systems. Simple electronic circuits are to be used as an experiment to exemplify the potential success that can be discovered from the development of a novel prognostic model that can efficiently estimate the RUL of one system based on the prognostics of another system.**

Keywords-Prognostic Model, Integradted System Health Management (ISHM), Degradation, Duality, Cuk Converter.

I. INTRODUCTION

Integrated System Health Management (ISHM) [1] is the next evolutionary step in condition based asset management, endeavoring to build automated prognostic and diagnostic systems to preserve and enhance the safety and readiness obtained from legacy Health and Usage Monitoring Systems. ISHM is to detect, diagnose, predict, and mitigate undesirable events caused by degradation, fatigue and faults in components over a certain period of time. For instance, the presence of such problems may occur during an important function related to a system's aircraft, regardless of whether the adverse event was caused by the subsystems. To properly address this problem, it is critical to develop technologies that can integrate large, heterogeneous distributed system [2], asynchronous data streams from multiple subsystems to detect a potential adverse event. The technologies would later be used to diagnose the cause of the event, foresee what consequences the event will have on the remaining useful life of the system (i.e., how it would jeopardize the entire system), and lastly take appropriate precautions to mitigate the event, if necessary [1].

Furthermore, effective estimation of the remaining useful life of devices and systems rely on development of prognostic models. This in turn requires extensive effort being made towards accelerating ageing mechanisms for each component, which ultimately enables us to prepare a sufficient amount of degradation profiles. This therefore makes it necessary to obtain the degradation profiles of every subsystem, including their individual components. This leads to a new degradation profile being devised every time a component is upgraded. The following degradation profile is calculated from either the accumulated damage or the data driven. Consequently, any changes made in the design of the system will both consume time and incur additional costs, considering that the prognostics model will need to be re-upgraded. It is thus apparent that the proposals discussed above are all expensive and time consuming processes that suffer from unreliability, noise, inaccuracies, etc [3].

To effectively overcome these problems, at the highest system level, a System- Level Reasoning (SLR) can be developed to at least provide the system with significant capabilities that can potentially decrease costs by assigning the system prognostics with a System Integrated Prognostic Reasoner (SIPR) [1][4]. A Vehicle Integrated Prognostic Reasoner (VIPR), for instance, is a NASA funded effort for developing the next generation VLRS. A typical functional module within the SLR is a System Reference Model. This System Reference Model divides the system into partitions; and provides the necessary relationships between subsystems for the inference process. This partitioning enables the inference engine to reuse and link the same prognostic models to multiple subsystems and further minimize certification and qualification costs [1][4].

In summary, various techniques and methods, such as neural network, fuzzy, statistics, semantic computing, graph theory etc. have been utilized for the development of ISHM. However, ISHM still suffers from problems related to inefficient models, uncertainties and inadequate reasoning. In addition, the development of prognostic models still remains to be very costly and time consuming. These problems however still exist, mainly because the prognostics of a system heavily relies on the physics of failure models and degradation profiles that are known to be either inaccurate, inconsistent or very noisy. We believe that the ISHM system will greatly benefit if the prognostic of a component and a system is perceived as a feature rather than a system or component, which allows us to develop the prognostics based on this specific feature of the system instead of having to worry about the physics of the components. An advantage of this approach is that it will enable SLR to develop prognostics for a new subsystem based on a collection of features (encompassing various models/patterns) already known from the previous prognostics of subsystems. In order to fulfill this task, SLR may need to employ various techniques, such as those that involve Soft Computing (SC) including (fuzzy and neural network) in its Inference Engine and System Reference Model units, so that the subsystems properties can be linked to one another. In this proposal, we expect that there may be a duality connection found between the prognostics of dual systems, assuming that the prognostics of the dual systems are also seen as their parameters and features.

The next section shall describe in more detail the prognostics in systems. The principles of duality in electrical systems, along with brainstorming the duality concept of system's prognostics, are covered in Section 3. Section 4 covers the prognostics of Cuk converter and its dual circuit via developed algorithms and simulations with details of test approaches in Section 5. Lastly, the conclusion is covered in section 6.

II. PROGNOSTICS

In condition-based maintenance, prognostics can be defined as a controlled engineering discipline that focuses on the estimation and prediction of the future course of a system or component that attempts to workout at what point it starts to slowly develop irregularities and faults to the point where it eventually malfunctions. As a result of such malfunctions, a system or component can hence no longer meet the desired performance expectation. The predicted lifecycle of a system or component is referred to as the Remaining Useful Life (RUL). RUL is an important concept that is used in decision making for contingency mitigation and maintenance. The prognostics of a system or component are constructed from various scientific techniques including: failure mode analyses, early detection of aging signs, and damage propagation models. Failure mechanisms are often used in conjunction with system lifecycle management to create prognostics and health management (PHM) disciplines. PHM is also sometimes referred to as system health management (SHM) or within the field of transportation applications; it is either referred to as vehicle health management (VHM) or engine health management (EHM). There are three main technical approaches related to building prognostic models which are broadly categorized into data-driven approaches, model-based approaches, and hybrid approaches [1][4][5].

A. Data-Driven Prognostics

Data-driven prognostics [6] are mainly based on pattern recognition and machine learning approaches in order to identify and detect changes and trends in system state phases. In regards to predicting trends in nonlinear systems, the classical data-driven methods include stochastic models, such as an autoregressive model, the bilinear model, the projection pursuit, etc. Soft computing techniques that involve using various types of neural networks (NNs) and neural fuzzy (NF) systems have also been commonly adopted to deal with data-driven forecasting of a system state [7]. The following prognostic approach concerns applications that have a complicated system; meaning that developing an accurate prognostic model of such a system will be expensive. So by using this particular approach to deal with complex systems will allow the prognostics of a system to be frequently set up much faster and cheaper as compared to other approaches. On the contrary, data driven approaches may have a wider confidence intervals than other approaches which mean it will require a substantial amount of data for training purposes [8].

Various strategies that are used to develop data-driven prognostics involve the analysis of either (1) modeling cumulative damage and then extrapolating out to a damage threshold, or (2) learning directly from the data relating to the remaining useful life.

Since individually failing systems is a lengthy and rather costly process, we thus seek to obtain a run-to-failure data which is the main fundamental setback, especially for new systems. In order to retrieve adequate data-driven prognostics, the accelerated aging data should be carefully extracted from a number of similar products by suitable measuring tools. This means that both quality and quantity aspects of the data driven prognostics will add to expenses; especially since the data sources may have been derived from a wide range of factors including temperature, pressure, oil debris, currents, voltages, power, vibration and acoustic signal, spectrometric data, as well as calibration and calorimetric data. It is therefore important to fully be aware of what parameters and signals are necessary to be measured, and which features must be extracted from noisy, high-dimensional data [6][7][8].

B. Model-Based Prognostics

The attempts made to incorporate a physical model of system which is (either accomplished via micro or macro levels) into the estimated remaining useful life (RUL) is known as model-based prognostics [5]. The micro level (also known as material level) is often referred to as damage propagation model which is a physical model that is integrated with a series of dynamic equations. These dynamic equations define the very relationships between damage and degradation of a system or component. They further define how the system or component is operated under environmental and operational conditions. As it's almost impossible to measure many critical damage properties, an alternative solution is to use sensed system parameters instead. However, there may be a possibility that the level of uncertainty and inaccuracy are increased. In spite of the uncertainty and inaccuracy added as a result of sensed system parameters, uncertainty management must be considered with the proper assumptions and simplifications, which may overcome the significant limitations caused by that approach [4][5][9].

In contrast to physical expressions used in micro-levels, macro-level models alternatively use mathematical models at a system level in order to define the relationship among system input, system state, and system measure variables. The mathematical model is often a simplified representation of the system. Simplification may help make prototyping faster; but the trade-off to this is that the coverage of the model is increased at the expense of reducing accuracy of a particular degradation mode. In addition, within a complex application, such as a gas turbine engine, there would be a lack of knowledge in attempting to develop the proper mathematics for all subsystems or components. Again, this adds uncertainty and inaccuracy, similar to micro-level models; which means simplifications would need to be accounted for by performing uncertainty management procedures [1][4][9].

C. Hybrid Approaches

In reality, having a purely data-driven or purely model-based approach is almost impossible. However, both models do include some aspects of one another mechanisms. Hybrid approaches intend to bring the strength of both 'data-driven' approaches and 'model-based' approaches into one prognostics strategy. The two well known categories of Hybrid approaches are, 1) Pre-estimate fusion and 2.) Post-estimate fusion. The first technique applied, hardly has any 'ground truth' data or 'run-to-failure' data available. The second technique is more suitable in situations where uncertainty management is required. This means that the second technique helps to narrow the uncertainty intervals of data-driven or model-based approaches while also improving accuracy [10][11].

III. Prognostics of Dual Systems

Duality is one of the fundamental properties of systems, so that it can be consistently seen in systems that have any kind of physics [12][13]. It has a captivating history in mathematics, engineering and science. Duality relations have been established between geometric objects, algebraic structures, topological constructs and various other scientific constructs. In electrical systems, duality relations have appeared in the core principles for any theorem in electrical circuit analysis in situations where there is a dual theorem that replaces one of the quantities with dual quantities; examples of dual quantities are current and voltage, impedance and admittance, meshes and nodes (shown in Table 1) [14].

TABLE I. Duality Principles in Electrical Systems

System	Dual of System
Voltage of nodes or across device	Current of branch or mesh
Current of branch or mesh	Voltage of nodes or across device
Resistor (R)	Conductivity (1/R)
Conductivity (1/R)	Resistor (R)
Capacitor (C)	Inductance (C)
Inductance (L)	Capacitor (L)
Voltage Source (Vs)	Current Source (Vs)
Current Source (Is)	Voltage Source (Is)
Kirchhoff's Current Law	Kirchhoff's Voltage Law
Kirchhoff's Voltage Law	Kirchhoff's Current Law
Mesh/Loop	Node
Node	Mesh/Loop

In regards to duality concepts, there will be a duality relationship between two electrical circuits if the parameters values and topologies of these two circuits are linked to one another based on details in Table 1. From a mathematical point of view, dual circuits have the same mathematical model except for having different parameters. Thereby we want to fully comprehend that if one was to consider that the prognostic of a system or component were to be seen as a parameter, it will thus mean that the prognostics of a system that have different topologies can be assigned to one another, while considering that the systems have the same mathematics model but with dual parameters as shown in Table 1. This provides us with the required facilities to develop the prognostics of a system based on the prognostics of its dual system.

From graph theory [12], it is well established that the behavior and function of a system can be recognized from knowing the topology of a system without the need of knowing the components and devices that are used in the system, considering that the nodes voltages and currents of branches in the circuit are known. Hence, it can be expected that graph theory provides us with the capability to construct the prognostic of a system based on its topology rather than concentrating on the devices and components that are integrated within the system. It is also expected that systems that have the same topology and mathematical models will also share the same prognostics no matter what components are included in the system. Therefore, it is possible to investigate how prognostic models can be designed from the topology of system rather than having to know physics of failure of a system. This makes the process of modeling the prognostics of a system much more ideal and realistic by saving a substantial amount of resources and time, since you wouldn't have to individually test each system to identify its prognostics.

Figure 1 shows an example of dual circuits. Using Kirchhoff's laws, it is evident that both circuits have the same form of mathematical model as shown in (1) for circuit in Figure 1-a; and (2) for circuit in Figure 1-b:

$$V_a \,.\, (1/R_1 + 1/R_2 + 1/R_3) = 0 \quad (1)$$

$$Ia \,.\, (R_1 + R_2 + R_3) = 0 \quad (2)$$

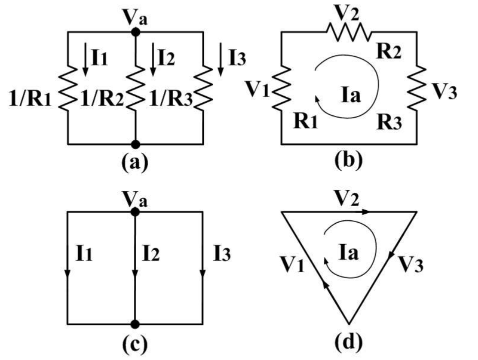

Figure 1. a) Cuk Converter, b) Dual circuit for Cuk converter in 2-a.

If for instance a degradation mechanisms is added, R_2 in circuit of Figure 1-b is aged as short circuit ($R_2 \rightarrow 0$), this is turned as ($1/R_2 \rightarrow \infty$) in circuit of Figure 1-a. This actually represents the duality principles shown in Table 1 in which the resistor is a dual of a conductive; or in regards to this example, it can be known as the short circuit being a dual of an open circuit.

The same rules can be used in more complex circuits where various components including capacitors and inductances are also used. The most critical point that needs to be worried about is the fact that degradation and failure mechanisms of dual components are not truly related to one another. Degradation mechanism of capacitor, for instance, is not related to degradation mechanisms of inductance, at all.

In order to deal with this problem, we rely on the well known physics principles, such as Ohm's and Kirchhoff's laws. In reference to these two laws, it's obvious that any electric component can be formulated by using voltage across the component and current through the component. Alternatively, in regards to basic principles in graph theory of circuit and system design, it is well known that the behavior of a system is fully formulated if voltage of all nodes and current through all branches in the circuit are also known. This means that no matter what components are used in the circuit, as long as all the voltages and currents are known, the behavior and function of circuit can be fully formulated. Figure 1-c and 1-d, respectively show the graph of the equivalent circuits in Figure 1-a and 1-b.

From a circuit level point of view, the components details do not necessarily need to be known in order to develop a prognostics model for a circuit. Practically, sensors are used to measure voltages, currents, temperature etc. This allows the experiences of a degraded circuit or system of any form, to be interpreted as a circuit not functioning properly, on the basis of the sensed values meaning. Although this principle can be applied for greater purposes, i.e., to design a device independent prognostic model, this paper will mainly aim to present a realization of duality principles for the development of prognostics for dual circuits.

In addition, duality concept has already been recommended for diagnosing faults. Reference [15] proposes a fault diagnoser based on the duality principle and the optimal control theory for linear systems. However, this paper will present duality applications in system prognostics.

IV. PROGNOSTICS OF CUK CONVERTER

This section shows how duality concept can be used to develop prognostic models for Cuk converter [16] and its dual circuit. The following simulations were all conducted with Matlab and Orcad. Schematic of Cuk converter and its dual circuit are shown in Figure 2-a and 2-b. We use certain values for Cuk converter devices as well as all the equations depicted in reference [16] for all the simulations in this paper. Cuk is a step-down/step-up converter that shares a similar switching topology with boost-buck. Thus, it presents the voltage ratio of a buck-boost converter:

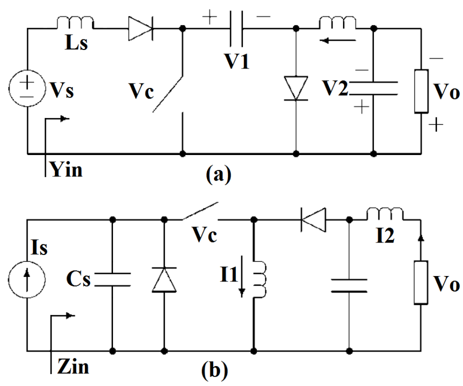

Figure 2. a, b) Resistive circuit with duality relationship, c,d) Graphs for circuits 1-a and 1-b.

$$v_o/v_s = D_s\,/\,(1\text{-}\ D_s). \quad (3)$$

where v_o is output voltage, v_g is the input voltage, D_s is the duty cycle of the switch $t_{on}/(t_{on}+t_{off})$; and t_{on} and t_{off} are durations for when the switch is on and off. Equation (3) is calculated from the principle of conservative energy and the fact that the inductor currents relate to the input and output currents. This equation shows that the output voltage can be controlled by maintaining the duty cycle of the switch. Depending on the switching scheme, output voltage can be higher or lower than the input voltage. The state equations for Cuk converter are:

$$x' = Ax + B_v g + B_c d \quad (4)$$

$$v_o = C_x$$

$$x = [v_2\ v_1\ i_2\ i_1]'$$

The Cuk converter has two inputs, a control input (V_c) and an input from the power supply (v_s) and one output (v_o). Therefore, matrix [A B C D] relates to 'state space matrices' for the open-loop model from the v_s to the v_o. Similarly, [A B_c C D] is the state space matrices from the control input d to the output v_o. Values for A, B, B_c, C, and D are given in [16]. The same equation can be extracted for dual circuit of Cuk converter in Figure 2-b; however, parameters are used in a dual form as shown in Table 1. Switches in Figure 2 are IGBT with a control voltage $V_{c.}$ Y_{in} and Z_{in} are input admittance and input impedance of Cuk circuit and its dual circuit.

In converters, components that are mainly damaged are IGBTs and capacitors. IGBT experience numbers of failure mechanisms, such as bond wire fatigue, bond wire lift up, corrosion of the wires, static and dynamic latch up, loose gate control voltage, etc. The resulting affects mentioned are too complex, but we assume that these failure mechanisms can cause IGBT to behave as either an open circuit on a collector-emitter or a device encountering malfunction on its gate-emitter control. For instance, IGBTs thermal junction is increased due to solder crack which turns to wire bond lift off that increases the resistor relating to the collector-emitter. On the other hand, hot carrier injection is increased due to electrical stress. This causes short circuit on the IGBTs gate-emitter junction. As a result of this failure, IGBT's gate controllability is missed (loose gate control voltage) that causes IGBT to malfunction. The result of this effect is an increase in current through collector-emitter which means that the resistor of collector emitter is decreased. Therefore, it can be realized that wire bond lift off and loose gate control voltage are failure mechanisms that presents some kind of duality relationship. While one of them increases the resistor, the other one decreases the resistor. Generally, we assume that IGBT's failure and malfunction mechanisms are parameters with duality relationships.

Figure 3 shows IGBT run to failure data for four different IGBTs. This data is too noisy and needs to be filtered, but still there are a number of states that can be seen in the data. These states refer to cracks or wires that were lifted up due to degradation mechanisms. The resulting effects are changes in the IGBT's function; and changes in the channel resistor of that IGBT. We assume that degradation is processed in a form of duality for Cuk and its dual circuit, so that if IGBT of Cuk experiences degradation towards its open circuit, IGBT of dual circuit of Cuk is degraded towards short circuit. By the time that the IGBTs are damaged, C_s and L_s are fully charged as well as the other energy storage components lose energy, so V_o would be 0. It is however impossible to have a real short circuit in IGBT, thus we assume that it may have happened when the current through the collector-emitter exceeds over its limit just before the IGBT is burned out.

Based on the level of accuracy, there are number of models for a real capacitor and an inductance. To simplify simulation, we assume that the capacitor and the inductance can both be modeled like Figure 4 for the purposes of this paper. These models will present duality relationship between capacitance and inductance while also presenting the energy lost by the resistors. R_1 typically has had very large values, while R_2 has a small value; but due to degradation, these resistors are changed towards either open or short circuits.

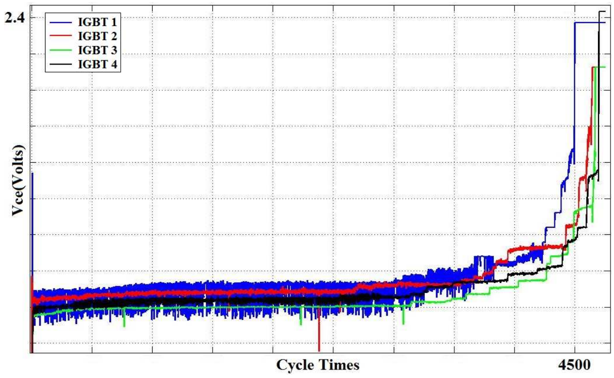

Figure 3. Run to failure data for four different IGBTs.

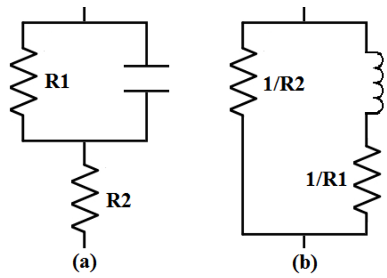

Figure 4. Real model for a) Capacitor, b) Inductance.

Figure 5 illustrates the proposed algorithm devised to develop this prognostics model. The same process that is possessed with different sets of run to failure degradation and malfunction profiles is repeated for both Cuk and its dual circuit. The components of the circuits are initially set to be in a good condition. Then as soon as the time step for the circuit is increased, the values of the components are changed by using a series of values provided in the degradation profile for the new time step. Signals, such as v_1, v_2, v_o, i_1, i_2, i_o, are measured at each time step phase. These signals are used for calculating systems properties, such as transfer functions, input and output impedances and admittances. Subsequently, the system degradation is turned according to changes encountered in the transfer functions ($Z_c(d,t)$, $Y_c(d,t)$, $Z_{dc}(d,t)$, $Y_{dc}(d,t)$). So where d is an index of a selected degradation profile, c is Cuk and dc is the dual circuit of the Cuk converter. Whenever d is altered, time step (t) is reset to zero which will reset the process of the circuit to a healthy condition for the new degradation scheme. By measuring the mentioned signals and parameters, it would be possible to realize how energy is transferred between capacitances and inductances; and how that transferred energy is lost when the system is also degraded.

We realized that if a degradation profile is used for Cuk, such that it's converted to a malfunction profile for its dual circuit so that the IGBTs in both circuits are always remained in dual forms; then a duality relationship would be seen

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between the transferred functions of these two circuits. For instance, $Z_c(t)$ is equal to $Y_{dc}(t)$. This is because as the degradation profile changes the IGBT of Cuk towards an open circuit; its malfunction profile also changes the IGBT of dual circuit towards a short circuit.

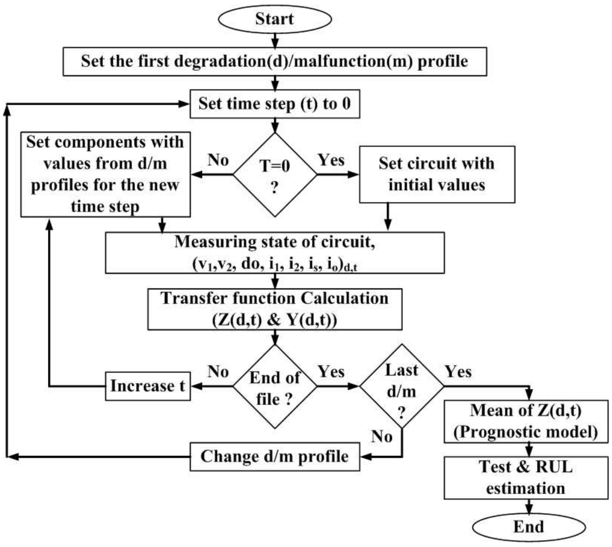

Figure 5. Algorithm used to develop prognostic model.

If the malfunction profile for dual circuit of Cuk is not extracted from the degradation profile of a Cuk circuit, then $Z_c(t)$ is not identical to $Y_{dc}(t)$. However, we come to a conclusion that if the whole process is repeated for number of different degradation and malfunction profiles and that the mean value of $Z_c(t)$ and $Y_{dc}(t)$ are used for comparison; leads to meaningful similarity patterns to be found between $Z_c(t)$ and $Y_{dc}(t)$. $Z_{mc}(t)$ can be used for the mean value of $Z_c(d,t)$ and $Y_{mdc}(t)$ can be used for the mean value of $Y_{dc}(d,t)$, in situations where m refers to the mean value. $Z_{mc}(t)$ and $Y_{mdc}(t)$ can be both used as prognostic models for Cuk and its dual circuit. However, these two transfer function are not exactly identical, but they would be more similar to one another if the process that is required to be executed to obtain the functions is repeated for various numbers of degradation and malfunction profiles for both circuits. By implementing more intelligent algorithms that use stochastic, neural network, fuzzy and other techniques instead of a simple mean value function will increase the accuracy of this prognostic model. Implementing such intelligent algorithms also reflects the future aim and direction of our research. Additionally, we should be aware that prognostics have always been a way to estimate the life time of devices and systems within different confidence levels. Confidence levels provide assurance, so that we can comfortably rely on the performance of an aged system. The point is the accuracy of prognostic models has always been under doubt and remains to be under margins of confidence levels. So in summary, by using the prognostic model of a system for other systems where similarities in their properties (like duality) are found, would give us a more accurate and reliable representation of the state and condition of the system or component. This is assuming that the prognostics are developed from adequate number of degradation profiles, and that they also have the right minimum and maximum confidence levels.

V. TEST APPROACH

The resulting prognostic model is tested with an additional degradation profile which is used as a test data to estimate the remaining useful life time for the converter. During the testing process, the prognostic model is stimulated via the samples derived from the test data. This causes the parameters of the prognostics model to change, which therefore leads to the degradation of the system. The accuracy of the degradation depends on the number of delayed and differentiated samples that are used to simulate the prognostic model as well its time step t sample.

The tests would be inaccurate, if the model was stimulated one sample at a time, despite there being durations in the test data where the samples remain almost the same. A more accurate testing is achieved, if differentiated samples are also used for stimulation. This thereby allows the prognostics model to follow the test data trend rather than only following one sample at a time.

Therefore to estimate the life time of system at each time interval, the model is stimulated with the sample at t and a set of differences. Once the life time of the system is estimated for that specific sample, it then selects the next sample from the test data provided for simulation, while also updating the differences. In addition to the system degrading at each time step, the next sample test (let's call it S^+) is also calculated from using the model's system. The simulation is then continued by stimulating the prognostic model using a calculated sample (S^+) which in turn degrades the model again and updates the calculated sample (S^+) with a new value. The same process is continued until S^+ reaches a threshold which refers to a specific class in the test data where the device is no longer in good condition for operation. We set the threshold to 7 based on the degeneration profile that we had available, Figure 3. Once S^+ reaches the threshold, the simulation continues with the next sample provided by the test data. This also requires the differences to be updated, accordingly. The life time for each sample of test data depends on the time that it takes for the model to reach the threshold from the time a new sample of test data has been selected for stimulation to the time that the calculated sample test reaches the threshold. This means that the stimulation for each time step starts with a new sample obtained from the test data. As this process is repeated with the sample calculated, the model also eventually degrades. Figure 6 shows a real and estimated RUL with %10 and %90 confidence levels.

VI. CONCLUSION

In conclusion, this paper shows that the prognostics of a system can be applied to other systems that share similar properties in the form of duality. A prognostic model is developed in the form of a time dependant transfer function where values are altered over a certain period of time based on the degradation mechanisms of a system's components. By having the prognostics assigned to a system's property reflects the duality connection of degradation and malfunction of system. This means that if the components of a system are aged, their dual components in the dual circuit will be faced with malfunction. The accuracy of the developed prognostic model is dependent on the number of available degradation profiles; and the method that is used to train the time dependant transfer function. The accuracy of this model is guaranteed and expressed within the minimum and maximum confidence levels. However, we presented our approach just for Cuk converter and its dual circuit, but it seems that the same technique can be used for systems that have slightly similar topologies, degradation mechanisms, and properties. Thereby, further research needs to be conducted for systems that are not in dual forms, especially for the purposes of exploring how the prognostic model of a system could be mapped to the prognostic model of another system.

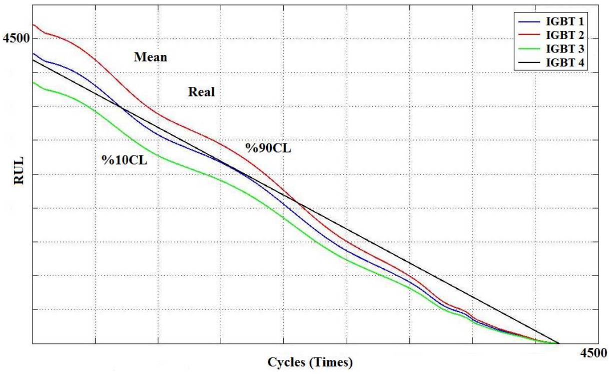

Figure 6. Resulting RUL after testing prognostic model with data test.

The advantage and usage of such a technique is emphasized in the implementation stage of the inference engine for System- Level Reasoning (SLR) and System Integrated Prognostic Reasoner (SIPR). In addition, it provides us with the facility to transfer degradation knowledge and experiences between systems. This means that the development of prognostics for huge systems, such as heterogeneous distributed systems used in applications like aircraft is much faster, while the cost assigned to accelerated aging tests and preparing degradation profile is decreased. We essentially intend on pushing forward with our research, in order to apply this technique to the development of the prognostic inference engine and reasoned for aircraft.

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