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Development and implementation of product sustainment simulator utilizing fuzzy cognitive map (FCM)

Benedict M. Uzochukwu Silvanus J. Udoka Femi Balogun

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Benedict M. Uzochukwu
Department of Technology,
Virginia State University, Petersburg, Virginia, USA
Silvanus J. Udoka
Department of Management, School of Business and Economics,
North Carolina Agricultural and State University,
Greensboro, North Carolina, USA, and
Femi Balogun
Department of Computer and Information Systems,
Livingstone College, Salisbury, North Carolina, USA

Abstract

Purpose – Managing product life cycle data is important for achieving design excellence, product continued operational performance, customer satisfaction and sustainment. As a result, it is important to develop a sustainment simulator to transform life cycle data into actionable design metrics. Currently, there is apparent lack of technologies and tools to synthesize product life time data. The purpose of this paper is to provide a description of how a product sustainment simulator was developed using fuzzy cognitive map (FCM). As a proof of concept, and to demonstrate the utility of the simulator, an implementation example utilizing product life time data as input was demonstrated.

Design/methodology/approach – The sustainment simulator was developed using visual basic. The simulation experiment was accomplished using a FCM. The Statistical Analytical Software tool was used to run structural equation model programs that provided the initial input into the FCM and the simulator. Product life data were used as input to the simulator.

Findings – There is an apparent lack of technologies and tools to synthesize product life time data. This constitutes an impediment to designing the next generation of sustainable products. Modern tools, technologies and techniques must be used if the goal of removing product design and sustainment disablers is to be achieved. Product sustainment can, therefore, be achieved using the simulator.

Research limitations/implications – The sustainment simulator is a tool that demonstrates in a practical way how a product life time generated data can be transformed into actionable design parameters. This paper includes analysis of a sample generated using random numbers. The lack of actual data set is primarily due to reluctance of organizations to avail the public of actual product life time data. However, this paper provides a good demonstration of how product life time data can be transformed to ensure product sustainment.

Practical implications – The technique used in this research paper would be very useful to product designers, engineers and research and development teams in developing data manipulation tools to improve product operational and sustainable life cycle performance. Sustainment conscious organizations will, no doubt, benefit from a strong comparative and competitive advantage over rivals.

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Originality/value – Utilizing the simulator to transform product life time data into actionable design metrics through the help of an efficient decision support tool like the FCM constitutes a step in supporting product life cycle management. The outcome of this paper alerts product designers on parameters which should be taken into account when designing a new generation of a given product(s).

Keywords Fuzzy cognitive map, Product life cycle management, Simulator, Sustainment

Paper type Research paper

Introduction

The search for new tools, methodologies, technologies and techniques to ensure the sustainment of products during their lifespan continues to pose significant challenges for product designers. This explains the urgency for developing tools that assist developers of products to mine and utilize product life time data to speed up technical data development for new products, and allow designers to focus on creating products with an eye on meeting the ever increasing and changing demands of the customer. An approach to creating value by means of converting information into knowledge was discussed by Kiritsis *et al.* (2003). The approach is known as Product Life cycle Management and Information tracking using Smart Embedded systems (PROMISE). PROMISE takes place at every stage of a product's operational life cycle. Consequently, perceived quality, efficiency and sustainability of a product are not only guaranteed but improved. The research proposed in Kiritsis (2004), PROMISE (2004), Kiritsis and Rolstadas (2005) allows all stakeholders in the various stages of the product life cycle to contribute meaningfully to the managing and controlling of product information and implementation. Product life cycle management has been variously discussed by Ameri and Dutta (2004), CIMdata (2002) and Datamation Limited (2002) as a strategic business approach for providing a shared platform for creating, organizing and disseminating product-related data across the spectrum of enterprise operations.

Hong-Bae *et al.* (2007) discussed how emerging technologies have utilized product life cycle management to gather and analyze product life cycle information and make informed decisions on numerous issues devoid of spatial and temporal constraints. These technologies have been known with several names such as smart tags (Qiu and Zhang, 2003), or intelligent product (Wong *et al.*, 2002; McFarlane *et al.*, 2003). The aim of utilizing these technologies is to make it possible to track product performance data in real time over the entire product life cycle, utilizing automated data collection device inserted into the product itself. In order to garner the full benefits of product life time tracking, data accumulation should commence from initial product deployment and continue throughout its useful life. It should be noted; however, that life cycle activities tracked from the middle to end phases of operational life may give limited visibility of a given product-related information. Consequently, decisions made using incomplete and inexact information can lead to inefficiencies in operations (IMTI, 2002).

The case example presented in this paper utilizes data accumulated from a specific model of fuel injector product line. In this example, the data pointed to the fact that the performance of the product did not meet the quality and reliability threshold for the product's specified life and operating conditions. Poor performance of the product thus resulted in escalating cost of ownership and maintenance burden, making it increasingly unprofitable to sustain the product. In order to adequately address this problem, the product development and design team must glean relevant performance data from the current product, as input to redesign the next generation of this product, with parameters that alleviate this sustainment burden.

Fuzzy cognitive map (FCM) was applied as a novel approach in this application area, to utilize data that had been gathered during the fuel injector's life time, from radio frequency identification (RFID) sensor, to model the performance of a redesigned model of the product. FCM is utilized as an efficient computing tool that supports a graphical representation of knowledge, providing visualization which can be used for explanation of a particular line of reasoning. Although there are other computational methodologies to represent knowledge with inference capability, such as the Bayesian belief network, decision tree models and artificial neural networks, the justification for the choice of FCM over other methods is its predictive capability. For each simulation step, the value of each factor used in this paper is calculated, taking into consideration the influence of the interrelated factor(s) and their assigned weights, using equation developed by Stylios and Groumpos (2000). During the development of the FCM, experts determine the direction of the correlation between two concepts, the sign convention and degree of correlation of the map of the system being modeled. After these are determined, the system can then be simulated. The outcome of FCM provides input to the product designers in making redesign or new design decisions. This approach is attractive because it can potentially resolve contradictory input parameters that may have been causes of product sustainment issues in the previous model.

Overview of the concept of product sustainment

Product sustainment refers to all activities necessary to keep an existing product operational in order to successfully complete an objective. The emphasis of sustainment is on the mission readiness of the product. Product or system sustainment in the context of this paper can therefore be described as those activities designed to meet the operational and performance readiness requirements in a cost effective and efficient manner. Sustainment also embraces assembly, reliability, maintenance, manufacture and improvement in product performance. Sustainment programs involving complex durable products (such as military weapon systems) require smart and new processes, new relationships, new technologies and a new mindset regarding product supportability. In support of this mindset, Mathaisel (2009) called for a system which will bridge the gap created by current systems that are solely designed and arranged as separate entities; and where an overwhelming emphasis is focussed on the system instead of the product.

Agripino *et al.* (2002) developed a Lean Sustainment Enterprise Model where the authors discussed maintenance, repair and overhaul (MRO) with the goal of consolidating and integrating sustainment functions. The authors hoped to achieve significant customer service levels while reducing total ownership costs. Mathaisel (2009) proposed an architecture for lean transformation. The architecture emphasizes change in repair processes, material support and management mindset. This is geared toward overhauling the industrial space needs to function with commercial efficiency in the mold of lean manufacturing. Ellmyer (2006) explored why the Air Force should consolidate the operational function of supply support, why it is needed, and what to do about it. The consolidation would provide a stable infrastructure when conflicts go from peace time to war time operations. Ellmyer posits that the Air Force must create a supply chain management enterprise that makes operations more efficient, more effective and reduce costs while providing sustained levels of weapon system availability.

Goh and Coleman (2003) presented a novel cognitive engineering approach to creating a framework that more fully captures the decision support needs of commercial aircraft gas turbine engine MRO organizations. They developed a broader set of computer-based decision support tools to meet various other decision support needs of the engine MRO community that includes fault prognostics, maintenance planning, scope of work and generation and configuration management. Using field studies of various airlines, engine MRO providers and engine manufacturers across North America, Asia-Pacific and Europe, the analyses presented in their paper offer a thorough understanding of the cognitive needs and the decision-making process in engine maintenance repair overhaul enterprises.

The simulator that was developed in this research, and presented in this paper reflects an implementation of bio-inspired design approach, mimicking a natural transfer of knowledge in humans, where product end of life (EOL) information can be harnessed and utilized to improve decisions at the beginning of life (BOL) of the next generation of the product. Automatic identification technologies such as RFID are utilized to accumulate performance data including product identity and its operational parameters. The simulator uses actual product performance data to mock up performance scenarios, seeking the most favorable combination of factors that would lessen the sustainment footprint of next generation product. The simulated outcomes can be utilized by designers to capture salient product sustainment issues which could then be incorporated in next generation product development or redesign. The bio-inspired design utilizes natural occurrence to proffer solutions for design problems. Vincent and Man (2002), for example, described how they imitated the design of pinecones for clothing such that the body temperature can better be regulated. Biomimetic design concepts have also been studied by Ayre (2003).

Simulator development

The sustainment simulator's user interface was developed using visual basic. The simulation experiment was accomplished using a FCM. The Statistical Analytical Software (SAS) tool was used to run structural equation model (SEM) programs that provided the initial input into the FCM and the simulator. The interactive environment for numerical computation, analysis and visualization was developed using MATLAB. Balogun (2009) illustrated that a hybrid of FCM and the Dempster-Shafer information fusion algorithm provides more accurate aggregated information in an emergency response command and control environment. The overarching implication is that information must be quickly and efficiently processed, analyzed and presented in a manner that will fully support critical decisions. The interface is made up of several frames that address specific areas of the process implementation. The first frame is the setup menu where chosen concepts are entered. In the event of a mistake, concepts can be removed using the appropriate button. The continue button takes the experimenter to the connection matrix frame where the matrix generated from the FCM is embedded. Following the outcome of the relational operators developed after comparing the RFID sensor data with the technical data, the current product state is determined and entered. By clicking the simulate button, the simulation process is carried out.

By clicking the "continue button" in the matrix frame, the product current state frame is activated. A screen shot of the sustainment simulator is shown in Figure 1. The following section explains how each window of the sustainment simulator is used as well as how data moves from one window to the next.

Window 1 allows the user to enter the desired parameters chosen for the study. In Window 2, all the chosen and entered parameters are lined up and confirmed. Changes can be made and mistakes corrected at this window. Window 3 is where the connection matrix of the chosen parameters is embedded. In Window 4, the frame

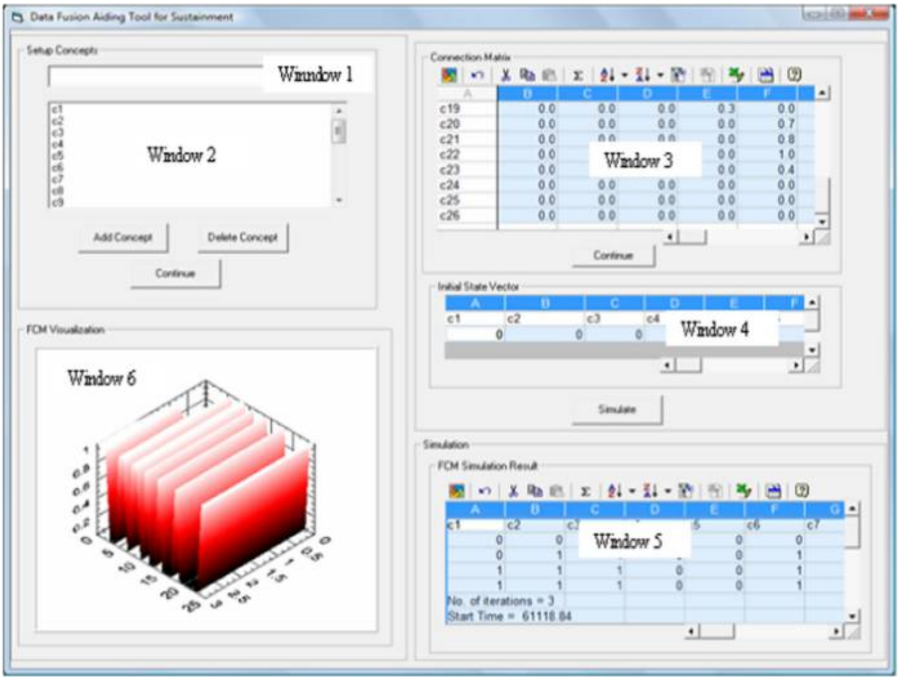

Figure 1.
Screen shot of Sustainment Simulator Interface

allows the current product state to be entered. Window 5 gives the result of the simulation process while Window 6 gives a visualization of the result of the process in three dimensional format. The first step in the simulation is to define and enter the input parameters or factors to be used in the FCM in the setup module. Typically, all the necessary product sustainment concepts are added in this screen.

Proof of concept

Product parameters

In the proof of concept, multiple variables associated with a durable product are evaluated. Each of the parameters or variables typically represents a given measurement that is associated the product's performance. In order to comprehend the more complicated combinations of relationships between various measurements or parameters, the application of multivariate data analysis methods becomes imperative. These multivariate analyses methods have the capability to simultaneously analyze multiple variables (Hair *et al.*, 2014). In this paper, the two multivariate methods that are used are SEM and FCM. A brief description of the two analysis tools is presented.

SEM

Chin (1998) referred to SEM as a statistical tool that incorporates unobservable variables or parameters (as shown in Table I) that are measured indirectly by what is known as indicator variables. According to Chin, the statistical tool also helps in facilitating the explanation of measurement errors in observed variables. The SEM was introduced for two purposes: first, to find out whether life cycle factors covary; and second, to develop a quantitative model which will be used in the FCM-based simulator.

Table I.
List of parameters

Parameters	Parameters
P_1 – Sustainment	P_{14} – Error rate
P_2 – Assembly	P_{15} – Field error rate
P_3 – Reliability	P_{16} – % technology insertion
P_4 – Robustness	P_{17} – Loss to variation ratio
P_5 – Disassembly	P_{18} – no. of times variation detected
P_6 – Sorting	P_{19} – % impact of noise factors
P_7 – Part connection	P_{20} – Part disassembly time
P_8 – Hand assembled part	P_{21} – Avg. items removed/time
P_9 – Avg. assembly time	P_{22} – tools required
P_{10} – Avg. no. of fasteners	P_{23} – % removal without damage
P_{11} – Chamfer angle	P_{24} – no. of material sorted
P_{12} – Mean time between Failure (MTBF)	P_{25} – % defect detected
P_{13} – Mean time to repair (MTTR)	P_{26} – type of tools required

This approach requires the gathering of applicable life cycle data; developing the initial theoretical model and associated structural equations. In defining why SEM technique is important, Maruyama (1998) observed that researchers want to know not only how well the factors explain a particular criterion, but also what specific factors are most important in predicting a particular goal. SEM is not only a powerful method for analyzing multivariate data, it gives an insight into statistical concepts in data analysis, the problem of causal inferences and the difference between reality and data (Cudeck *et al.*, 2001).

In this research, SEM is used to associate one product life time factor with others to determine which factors are more important in predicting or explaining a particular sustainment goal or criterion. SEM provides the capability to combine qualitative cause-effect information combined with statistical data, to provide a quantitative assessment of cause-effect relationships among design factors of interest for a given product. Hair *et al.* (2010, 2011) discussed two approaches to estimate the relationships in a SEM.

An initial theoretical SEM model was developed, tested and analyzed. After analyzing the initial theoretical SEM model, a modified model was constructed, tested and analyzed. A number of statistical indices such as goodness of fit index are used to interpret the experimental implications. The initial and modified theoretical models are then compared. The data utilized to test the model in this research was randomly generated using Monte Carlo Simulation.

FCM

Kosko (1992) and Stylios and Georgopoulos (2008) offer an alternative knowledge fusion scheme, FCM. A FCM is utilized to represent knowledge and inference that emphasizes the connections of concept or factors as basic units for storing knowledge. In this application, the FCM structure represents the robustness of the designed system. The most useful aspect of the FCM is its prediction capability. The inclusion of FCM is, therefore, a strategy to improve data quality. Typically, FCM demonstrates the relevance of product life time data for the benefit of design improvement. Derivable benefits could lie in the trustworthiness of the collected data, processes enabled, accuracy of predictions and analysis, as well as a good decision support tool. The framework developed supports the reduction of sustainment footprints.

Data flow from SEM to FCM

A functional causal model consists of a set of equations of the form:

$$x_i = f_i(pa_i, u_i), i = 1, \ldots, n, \quad (1)$$

where x_i is SEM problem; pa_i is set of variables judged to be immediate causes of x_i; u_i is errors (or disturbances) due to omitted factors.

Typically, a set of equations in the form of Equation (1), represent a decision-making mechanism referred to as SEM. The structural models are characterized by the solutions of each individual equation (Pearl, 2000). The implication of this is that any subset of structural equation is, by themselves provide a valid model of reality.

The parameters, $P_1, \ldots, P_{26}$ are taken as the nodes and causalities (connecting arrows) as the edges. The FCM models the parameters that best describe the product performance parameters, used as measures of sustainment. As more information becomes available, other parameters can be added to provide a more holistic and realistic and understanding of the product. Before defining the structure of the relationships, notation of the parameters utilized in the analysis is presented in Table I.

The example presented here is for demonstration of the data flow from the SEM to the FCM. Typically, FCMs model real world situations as a collection of concepts and causal influences or relations between the concepts. For example, the directed edge e_{ij} from P_i to P_j displays how much P_i causes P_j. In effect, the edges e_{ij} take the values in the fuzzy causal interval [−1, 1]. $e_{ij} = 0$ gives an indication of no causal influence, while $e_{ij} > 0$ indicates that an increase in P_i increases P_j and $e_{ij} < 0$ indicates that an increase in P_i decreases P_j.

Clamping concepts and an iterative vector-matrix multiplication procedure are used to assess the effects of disturbing or deviate influences on the state of a model to reveal if there are system implications. The number of iteration the simulator goes through depends on a number of factors. First, if the simulation reaches fixed point attraction where a fixed pattern, based on the initial state vector (ISV) is observed, the iteration stops. Second, if the simulation exhibits several repeating patterns, the implication is that it has reached a limiting cycle and it stops. Third, the simulation iteration process stops if a chaotic mode is reached. This means that no patterns could be discerned implying that it is not possible to predict the effect of the ISV.

An example of FCM developed from the output of SEM is presented in Figure 2. From the graphical representation, a connection matrix is developed. Since there are a total of 26 parameters, the connection matrix is a 26×26 matrix.

Typically, this can be represented as:

$$E = [A_y] 26 \times 26 \quad (2)$$

A SEM map is used to manually demonstrate the inner workings of the FCM as a predictor of sustainment. The FCM approach used in this demonstration is a two-level FCM approach. The first level uses the FCM to predict the values of the five product life cycle parameters (P_2-P_6) using parameters P_7-P_{26}. The second level uses the FCM to predict sustainment (P_1) using P_2-P_6. In this demonstration example scenario, the absolute values of the edge strengths were used.

The predictions with respect to changes in the state behavior of a model are determined by the activation of individual parameters chosen for the simulation.

Each parameter of interest that is activated is set to 1 and all the other parameters are set to the value of 0. In this circumstance, the input vector is stated as $1xn$ vector,

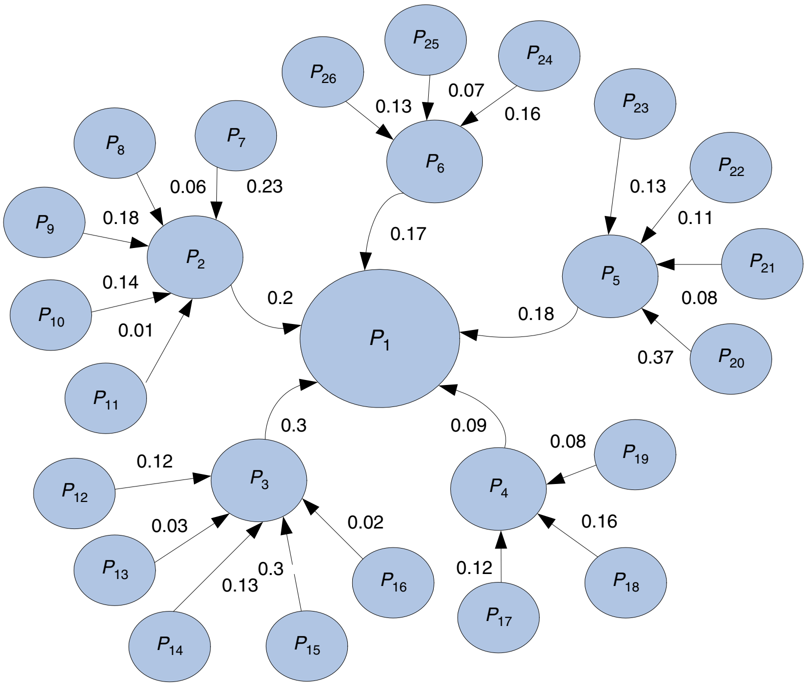

Figure 2.
FCM developed using SEM

where n is the number of parameters involved. The output, O is a vector of order $1xn$. By the binary conversion of the output vector O, what is derived is:

$O(x) = 1$ if $x > f$, where f is the threshold value and 0 otherwise.

$$O(x) = \begin{cases} 1 \; if \; x > 1 \\ 0 \; otherwise \end{cases} \tag{3}$$

By studying the final state of the iterations, an inference can be made from the model.

Predicting assembly, P_2. Let the initial product state, $I_0 = [0\ 1\ 1\ 1\ 1\ 1]$. This means that parameters $P_2 = 0$, $P_7 = 1$, $P_8 = 1$, $P_9 = 1$, $P_{10} = 1$ and $P_{11} = 1$. The connection matrix, C, for the FCM is defined as:

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0.23 & 0 & 0 & 0 & 0 & 0 \\ 0.06 & 0 & 0 & 0 & 0 & 0 \\ 0.08 & 0 & 0 & 0 & 0 & 0 \\ 0.14 & 0 & 0 & 0 & 0 & 0 \\ 0.01 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Iteration 1.

$I_1 = I_0 \times C = [0.52\ 0\ 0\ 0\ 0\ 0]$.

Comparing I_1 to threshold value $= 0.5$, $I_1 = [1\ 0\ 0\ 0\ 0\ 0]$. This means that $P_2 = 1$.

Clamping I_1

$I_1 = [1\ 1\ 1\ 1\ 1\ 1]$

Since I_1 is not equal to I_0, we proceed to iteration 2.

Iteration 2

$I_2 = I_1 \times C = [0.52\ 0\ 0\ 0\ 0\ 0]$.

Comparing I_2 to threshold value, 0.5, $I_2 = [1\ 0\ 0\ 0\ 0\ 0]$.

Clamping I_2, $I_2 = [1\ 1\ 1\ 1\ 1\ 1]$.

Since $I_2 = I_1$, iteration stops. The final product state is $I_2 = [1\ 1\ 1\ 1\ 1\ 1]$ which implies that $P_2 = 1$

Parameters P_3, P_4, P_5 and P_6 are predicted using the same procedures described for P_2.

Predicting P_3. Let the initial product state, $I_0 = [0\ 1\ 1\ 1\ 1\ 1]$. This means that parameters $P_3 = 0, P_{12} = 1, P_{13} = 1, P_{14} = 1, P_{15} = 1$ and $P_{16} = 1$. The connection matrix, C, for the FCM is defined as:

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0.12 & 0 & 0 & 0 & 0 & 0 \\ 0.03 & 0 & 0 & 0 & 0 & 0 \\ 0.13 & 0 & 0 & 0 & 0 & 0 \\ 0.30 & 0 & 0 & 0 & 0 & 0 \\ 0.02 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The final product state is $I_2 = [1\ 1\ 1\ 1\ 1\ 1]$. This means that P_3 is 1.

Predicting P_4. Let the initial product state, $I_0 = [0\ 1\ 1\ 1]$. This means that parameters $P_4 = 0$, $P_{17} = 1$, $P_{18} = 1$ and $P_{19} = 1$. The connection matrix, C, for the FCM is defined as:

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0.12 & 0 & 0 & 0 \\ 0.16 & 0 & 0 & 0 \\ 0.08 & 0 & 0 & 0 \end{bmatrix}$$

The final product state is $I_2 = [0\ 1\ 1\ 1]$. This means that P_4 is 0.

Predicting P_5. Let the initial product state, $I_0 = [0\ 1\ 1\ 1\ 1]$. This means that parameters $P_5 = 0, P_{20} = 1, P_{21} = 1, P_{22} = 1$ and $P_{23} = 1$. The connection matrix, C, for the FCM is defined as:

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0.37 & 0 & 0 & 0 & 0 \\ 0.08 & 0 & 0 & 0 & 0 \\ 0.11 & 0 & 0 & 0 & 0 \\ 0.13 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The final product state is $I_2 = [1\ 1\ 1\ 1\ 1]$. This means that P_5 is 1.

Predicting P_6. Let the initial product state, $I_0 = [0\ 1\ 1\ 1\ 1]$. This means that parameters $P_6 = 0$, $P_{24} = 1$, $P_{25} = 1$, and $P_{26} = 1$. The connection matrix, C, for the FCM is defined as:

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0.16 & 0 & 0 & 0 \\ 0.07 & 0 & 0 & 0 \\ 0.13 & 0 & 0 & 0 \end{bmatrix}$$

The final product state is $I_2 = [0\ 1\ 1\ 1]$. This means that P_6 is 0.

Predicting sustainment, P_1

In predicting P_1, let the initial product state, $I_0 = [0\ 1\ 1\ 0\ 1\ 0]$. This means that parameters $P_1 = 0$, $P_2 = 1$, $P_3 = 1$, $P_4 = 0$, $P_5 = 1$ and $P_6 = 0$. The connection matrix, C, for the FCM is defined as:

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0.23 & 0 & 0 & 0 & 0 & 0 \\ 0.06 & 0 & 0 & 0 & 0 & 0 \\ 0.08 & 0 & 0 & 0 & 0 & 0 \\ 0.14 & 0 & 0 & 0 & 0 & 0 \\ 0.01 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The final product state is $I_2 = [1\ 1\ 1\ 0\ 1\ 0]$. This means that P_1 is 1 as shown in Figure 3. Therefore, the product is sustainable.

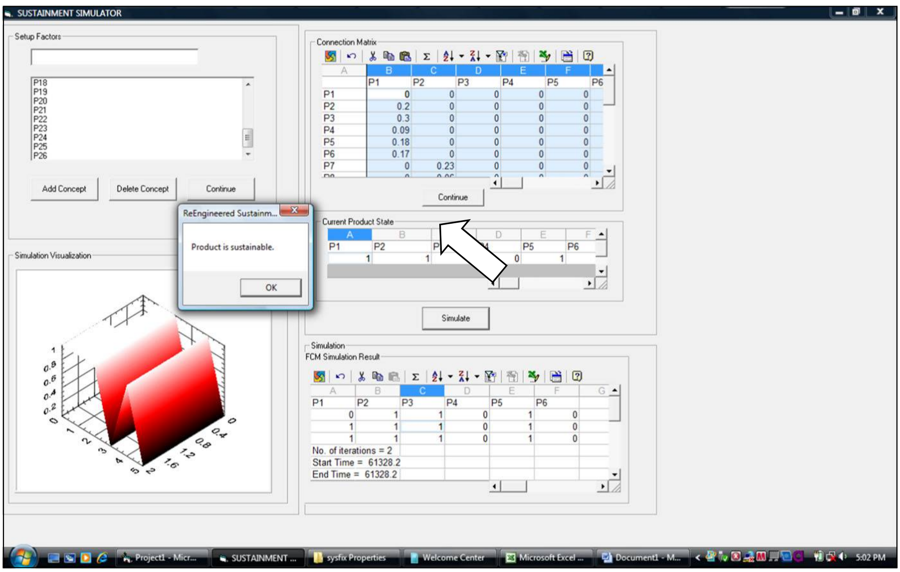

Figure 3.
FCM screen shot for *P*1

Generation of data and experimentation

The output of the simulation experiment allows for concise conclusions since the random number data set generated by Monte Carlo mimics real world situations. In this section, the outputs of the experiments are summarized, actionable insights offered and conclusions drawn. In effect, two different data sets were generated.

A total of six different threshold values were used during each of the simulation runs. The results of the two simulation experiments at the same threshold value were compared to show their impact on a particular simulation scenario. In the second set of simulation experiments, a large sample data set was used. In the simulation example, let $A^0 = (000000000100001011110001100)$ be an ISV in the FCM. The value of each parameter is typically influenced by the values of other connected parameters with the corresponding causal weights and by its previous value (Jang and Sun, 1995). The value A_j for each parameter P_j is therefore, calculated by equation:

$$A_i(t+1) = f\left(A_i(t) + \sum_{J=1}^{N} A_j(t).E_{ji}\right) \tag{4}$$

where $A_i(t)$ is the value of parameter P_i at step t; $A_j(t)$ is the value of parameter P_j at step t; E_{ji} is the weight of the interconnection from parameter P_j to parameter P_i; f is the threshold function that squashes the result of the multiplication in the interval [0, 1].

This equation gives an indication that parameters in the FCM are free to interact; at every step of the iteration that every parameter has a new value. When $P_{10,17,18,19,23,24}$ is activated, the value is set to 1 and when not activated, the value is set to 0. As soon as the FCM reaches equilibrium, the activation value generates the strength of the factors used for a given scenario.

On reaching equilibrium, the FCM activation levels are transformed back to the corresponding real values. Typically, it goes through several iterations over a given period of time to arrive at the final state vector as the output. For example, the final state vector for $A^1 = 100100000010000101110001100$ indicates that this particular iteration can support product sustainment as indicated by 1 at the beginning of A^0. The value of each parameter or concept is influenced by the values of the parameters or concepts connected with the corresponding causal weights and by its previous value.

Since equilibrium values can affect decisions, Kottas *et al.* (2004) proposed a method for computing equilibrium values in FCM. They state that in any complex system that is represented by a FCM, activities that indirectly affect each other exist and consequently, their influence may not be negative or positive. The FCM can be converted to a new FCM, which typically, has an equal number of nodes but with a change in relationship. With this slight change in relationship, they can represent only the maximum positive and negative effect one node has to the other. In this case, the notion of examining a FCM with only one positive or negative effect should be discounted.

Simulation run

The sustainment simulator is used to execute all the simulation runs. A graphical user interface affords the user the opportunity to easily enter key parameters, run simulations and from the output, gauge the sustainability or otherwise of a product. An overview of the simulator's functionalities has been discussed earlier. In the following paragraphs, a description of the simulation runs is provided.

Two different runs of 150 simulations each were carried out. In total, 25 ISV values were used to simulate product sustainability using six different threshold values. In total, 300 simulation runs were conducted using the same connection matrix. Each parameter has a value in the interval (0, 1). In Table II, the result of the first simulation using the threshold value of 0.5 is displayed.

The table shows the ISV and its final outcome. At the threshold value of 0.5, prediction level was 100 percent. The final state vector was used to determine whether or not the product was sustainable by inspecting the value of the concept variable 1.

Discussion

A number of conclusions can be drawn from this paper. Product sustainment once deployed, continue to be a significant challenge to product designers. The provision of solutions to product sustainment challenges can take advantage of numerous strategies, tools, frameworks or methodologies. These strategies can counterbalance issues that impact product operational and support costs, product life cycle challenges, fulfilment of customer and producer expectations, ownership cost issues, maintenance burden and profitability.

The sustainment simulator provides general descriptions of the major steps and issues involved in transforming product life cycle data to actionable information for product sustainment from the early product development and design stages. Overall, the framework uniquely provides an integrated process and structure that allows for the harnessing of dynamic data throughout the operational life of a designed product as input to development of products with significantly reduced sustainment footprint. Apart from providing a total support structure for continuous performance evaluation of product sustainment parameters, the framework affords product designers the benefit of real-time design support and planning as well as remarkable ability to make instant design changes based on sustainment needs and to be responsive to the dynamic nature of product operational and usage environment. It is anticipated that this framework will be of immense help to all levels of design and product development function, providing a fuller understanding of performance parameter interactions and how they relate to a product's operational performance. This knowledge can also be a basis for more coordinated product development decision-making process.

Decision support systems are very useful when making important product design decisions. As a result, such systems can improve product's tactical and strategic effectiveness. This requires selecting the best combination of strategies from a given set of alternatives for purposes of attaining stated objectives. Once the design inputs are known, the designers must be provided quantifiable input to enhance their choices in order to meet design goals targeted at ensuring sustainment.

Interpretation of results

The product is sustainable if the concept variable 1 had the value of 1 in the final state vector. A second set of simulations using the same initial connection matrix generated and Monte Carlo random number generator was conducted. The objective of carrying out a second set of simulations was to see how well this second set would compare with the first simulation run, using the same connection matrix and with the same threshold functions. Table III shows the level of success in achieving product design for sustainment. The table shows that as the threshold value

Sim no.	Initial state vector	Final state vector
1	0 0 0 0 0 0 00 0 1 0 00 0 1 0 1 1 1 0 0 0 1 00	1 0 0 1 0 0 1 0 0 0 0 1 0 1 1 1 0 0 0 1 1 0 0
2	0 0 0 0 0 0 1 0 1 0 0 00 1 1 0 1 1 0 0 0 0 1 00 0	1 0 0 1 0 1 0 0 0 0 1 1 0 1 1 0 0 0 0 1 0 0 0
3	0 0 0 0 0 0 1 1 1 0 0 10 1 0 0 1 1 1 0 1 1 1 11 0	1 1 1 1 1 0 1 1 1 0 0 1 0 1 0 0 1 1 1 0 1 1 1 1 1 0
4	0 0 0 0 0 0 1 0 1 0 1 00 0 0 1 1 1 1 0 0 0 1 00 1	1 1 0 1 0 1 1 0 1 0 1 00 0 0 1 1 1 1 0 0 0 1 00 1
5	0 0 0 0 0 0 1 0 0 1 1 00 1 0 0 1 0 0 1 0 0 1 01 0	1 0 1 1 1 0 1 0 0 1 1 00 1 0 0 1 0 0 1 0 0 1 01 0
6	0 0 0 0 0 0 1 1 1 1 1 10 0 1 1 1 1 0 0 1 1 0 00 0	1 1 1 1 1 0 1 1 1 1 1 10 0 1 1 1 1 0 0 1 1 0 00 0
7	0 0 0 0 0 0 1 1 1 1 1 11 0 1 0 1 0 1 1 0 0 0 01 1	1 1 0 1 1 1 1 1 1 1 1 01 0 1 0 1 0 1 1 0 0 0 01 1
8	0 0 0 0 0 0 0 1 0 1 1 11 1 1 1 1 1 0 0 0 1 1 11 0	1 0 1 1 1 0 0 1 0 1 1 11 1 1 1 1 1 0 0 0 1 1 11 0
9	0 1 1 1 1 1 0 1 1 0 1 01 1 1 1 1 1 1 0 1 0 1 10 1	1 1 1 1 1 1 0 1 1 0 1 01 1 1 1 1 1 1 0 1 0 1 10 1
10	0 0 0 0 0 0 1 0 0 0 1 00 1 0 1 1 1 0 1 1 1 1 00 0	1 0 1 1 1 0 1 0 0 0 1 00 1 0 1 1 1 0 1 1 1 1 00 0
11	0 0 0 0 0 0 1 0 1 1 0 11 1 1 0 1 1 0 0 0 1 0 01 0	1 1 1 1 1 0 1 0 1 1 0 11 1 1 0 1 1 0 0 0 1 0 01 0
12	0 0 0 0 0 0 0 0 0 1 0 00 0 0 0 1 0 0 0 1 0 1 11 0	1 0 0 1 1 0 0 0 0 1 0 00 0 0 0 1 0 0 0 1 0 1 11 0
13	0 0 0 0 0 0 0 0 0 1 0 11 1 1 1 0 0 1 0 0 1 0 10 0	1 0 1 0 1 0 0 0 0 1 0 11 1 1 1 0 0 1 0 0 1 0 10 0
14	0 0 0 0 0 0 1 1 0 0 1 01 1 1 1 1 1 1 1 1 1 0 11 0	1 0 1 1 1 0 1 1 0 0 1 01 1 1 1 1 1 1 1 1 1 0 11 0
15	0 0 0 0 0 0 0 0 0 1 1 10 1 1 0 1 0 0 1 1 0 0 10 1	1 0 1 1 1 1 0 0 0 1 1 10 1 1 0 1 0 0 11 0 0 10 1
16	0 0 0 0 0 0 1 0 0 1 0 01 0 0 0 1 0 1 0 0 1 0 00 0	1 0 0 1 1 0 1 0 0 1 0 01 0 0 0 1 0 1 0 0 1 0 0 0 0
17	0 0 0 0 0 0 1 1 1 0 0 01 0 1 1 1 0 0 1 0 1 0 01 1	1 1 0 1 1 1 1 1 1 0 0 01 0 1 1 1 0 0 1 0 1 0 01 1
18	0 0 0 0 0 0 1 1 0 1 0 10 0 0 1 1 0 1 0 1 1 0 11 0	1 1 1 1 1 0 1 1 0 1 0 10 0 0 1 1 0 1 0 1 1 0 11 0
19	0 0 0 0 0 0 0 1 0 1 0 10 1 1 1 1 0 1 1 0 1 0 00 0	1 0 1 1 1 0 0 1 0 1 0 10 1 1 1 1 0 1 10 1 0 00 0
20	0 0 0 0 0 0 0 1 1 1 0 00 1 1 0 1 1 1 0 0 0 0 00 1	1 1 1 1 0 1 0 1 1 1 0 00 1 1 0 1 1 1 0 0 0 0 00 1
21	0 0 0 0 0 0 0 1 0 1 1 00 1 1 1 1 0 1 0 0 0 0 01 0	1 0 1 1 0 0 0 1 0 1 1 00 1 1 1 1 0 1 0 0 0 0 01 0
22	0 0 0 0 0 0 1 1 0 1 1 01 0 0 1 0 1 0 0 1 0 1 0 1 0	1 1 0 0 1 0 1 1 0 1 1 01 0 0 1 0 1 0 0 1 0 1 01 0
23	0 0 0 0 0 0 1 0 0 1 0 00 1 1 0 1 0 0 0 0 1 1 11 0	1 0 1 1 1 0 1 0 0 1 0 00 1 1 0 1 0 0 0 0 1 1 11 0
24	0 0 0 0 0 0 1 1 0 1 1 10 0 0 0 0 0 0 0 1 0 1 11 1	1 1 1 0 1 1 1 1 0 1 1 10 0 0 0 0 0 0 0 1 0 1 11 1
25	0 0 0 0 0 0 1 0 1 1 0 10 0 1 0 0 0 1 0 0 0 0 01 1	1 1 1 0 0 1 1 0 1 1 0 10 0 1 0 0 0 1 0 0 0 0 01 1

Table II. First simulation results at threshold value 0.5

increases from 0.5 to 1.0, the percent sustainment rate decreases. The product designer must then use the appropriate level of threshold value for their desired level of sustainability.

When threshold value of 0.5 was used, the first simulation run yielded 100 percent sustainment accuracy. In the second simulation run, 96 percent sustainment accuracy was derived. A combination of different set of parameters accounted for this difference. Likewise, a threshold value of 0.6 yielded a sustainment accuracy of 96 percent in the first simulation run while 92 percent sustainment accuracy was generated in the second simulation run.

The process for generating the simulation data begins with RFID sensor generated data. Causal influences are established and reviewed. These data are fed via the graphical user interface to the simulator. After establishing a suitable threshold function, the ISV is

Threshold	Percentage sustainment success rate Simulation 1 (%)	Simulation 2 (%)
0.5	100	96
0.6	96	92
0.7	84	60
0.8	84	32
0.9	56	16
1.0	8	12

Table III. Percent sustainment success rate by threshold value of 0.5

set and the simulation run. This approach will help in the understanding of any underlying issues inherent in the formation of each causal node. Using Equation (5), the number of data points is derived. Typically, an initial input activates the matrix. The initial state of the factors is entered as a fuzzy vector and is allowed to reverberate through the system until it converges on a limit cycle. The limit cycle may be a point of equilibrium, a point of solution, a cyclical attractor or a point of chaos. The number of data points can be calculated using the following equation (Kosko, 1993):

$$\text{Number of data points} = P(P+1)/2 \tag{5}$$

where $P =$ number of manifest variables that is being analyzed. Using the above equation, a total number of 26 data points was established. The number of parameters to be estimated is determined using this total number of 26 data points that is used for this data analysis. In this instance, the number will be made up of all path coefficients, variances and covariances. SEM was performed, using SAS analysis, to test the theoretical model. Generally, all analyses were conducted using parameter estimation-based maximum likelihood methodology and were performed on the covariance, variance matrix. The results show if the causal model fits the data. Other test indices are also examined. The path coefficients were checked to see whether any of the paths in the theoretical model should be expunged based on the significance of the path. Some existing paths were eliminated from the model which suggests that not all of the life cycle factors used in the preliminary model are essential to support product sustainment. Adjustments could be made to the model as necessary. However, changes cannot be made for change sake but only when they are beneficial and has the potential to advancing product sustainment objectives.

Potential application areas

Due to the complexity of factors that impact product sustainment once deployed, the sustainment simulator serves as a viable tool for simplifying and harmonizing various product design parameters in a way that helps predictability of intensity and associated cost of product sustainment. This research provide a framework for product life cycle and usage data to be captured, mined and transformed in real time into actionable design and redesign information. This promises to benefit of product design improvement efforts, real-time product assessment and predictive maintenance improvement. This approach will be most beneficial for organizations using real-time data tracking devices like RFID technology and other data accumulation devices. Using these technologies, product designers can gather product life time mission critical data like configuration information, maintenance history as well operational environment performance. Makers of various complex durable components and products that can be tracked will benefit from this tool.

The tool will be applicable to a wide range of products and organizations. Regardless of the type of product and nature of the organization, the simulator will harmonize and integrate organizational data into a single platform for analysis. The outcome of this process will be increase in operational efficiency in data utilization. The impact on product sustainment footprint will manifest itself in areas such as cost of ownership, profit margin, system efficiency and effectiveness, among others.

Conclusion

Product sustainment demands that considerations for decreasing sustainment footprint be integral to the planning and management activities during early product design and development in order for it to be realized during the product's life cycle operation. This paper has developed and discussed a robust, scalable and adaptive tool to effectively filter product life time information to designers to impact their decisions during redesign or new design cycles. This addresses product life cycle challenges like maintenance burden reduction, maintenance efficiencies and total product cost of ownership, operational performance and ultimately, customer satisfaction. The development of this tool becomes even more important because of the apparent lack of technologies and tools to synthesize product life time data. In this research paper, our goal is to fill this gap. Accordingly, we provided an overview of the challenges facing product sustainment and how data collected from a product's operational life cycle can be a catalyst for improving mission readiness of a component or product. We also focussed on product data management and synthesis challenges which motivating the main focus of our work, to develop a tool that can turn life cycle generated data into actionable design input for sustaining the next generation of a product.

The simulator development process utilizing SEM and FCM was based on underlying natural transfer of knowledge in humans where product EOL information can be harnessed and utilized to improve decisions at the BOL of the next generation of the same product. In the proof of concept, the SEM was used to find out whether life cycle factors covary and also to develop a quantitative model for the sustainment simulator. FCM was used effectively as a decision support tool for synthesizing data into more useful and actionable formats because of its predictive capability. Because it models the causal reasoning in a design decision problem, it represents the ways in which data and information can be used to arrive at a decision. Contained within the structure of the map is a hierarchy of concepts. At the most basic level is the data about the operational environment in which the product operates. Using the FCM also represents a model of the product Sustainment system and surrounding challenges. Given the decisions and environmental attributes present, FCM can be used to predict a possible final state for the product or the system.

Our goal to fill data synthesis gap have led to the development of a product sustainment simulator. In this study, we have also successfully utilized SEM and FCM tools to develop data which formed the cornerstone of the sustainment simulator. We made a business case for this tool because of its potential to reduce product cost of ownership, improve life time operational performance and ensure mission readiness. This will be a catalyst for future researchers to develop the next generation of product sustainment simulators.

Utilizing the simulator to transform raw data into an actionable design metric through the help of an efficient decision support tool like the FCM constitute a significant step for supporting product life cycle management and sustainment. This paper, therefore, has successfully developed a methodology to clean, filter and transform life cycle generated data into actionable design parameters.

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About the authors

Benedict M. Uzochukwu is an Assistant Professor and Program Coordinator, Information and Logistics Technology at the Virginia State University. His research interests include sustainment, logistics, supply chain management, life cycle and embedded systems, systems integration and management of technology systems. He has a PhD degree in Industrial Engineering from the North Carolina A&T State University; Greensboro. He is a registered member of Institute of Industrial Engineers (IIE), Society for Engineering Management (SEM), Society for Health Systems (SHS) and Association of Technology Management and Applied Engineering (ATMAE). He is also a member of Alpha Pi Mu and Phi Kappa Phi Honors society. Benedict M. Uzochukwu is the corresponding author and can be contacted at: buzochukwu@vsu.edu

Silvanus J. Udoka, PhD, is a LANGURE Senior Fellow, Department of Management Chair and Associate Professor with joint appointment in the Department of Management and the Department of Industrial and Systems Engineering at the North Carolina A&T State University. He earned a PhD in Industrial Engineering and Management from the Oklahoma State University. His research interests are in the areas of interactive visualization and visual depiction, immersive 3-D (I-3D) environments; robotics applications, automation and integrated manufacturing systems engineering; design for sustainment; and Six Sigma and lean enterprises. He is an active member of Society of Manufacturing Engineers (SME), Institute of Industrial Engineers (IIE) American Society of Engineering Education (ASEE), Alpha Pi Mu, Tau Beta Pi, Phi Kappa Phi and the Order of the Engineer.

Dr Femi Balogun is a Professor and Chair of Computer Information Systems at the Livingstone College, Salisbury, North Carolina. He has over 30 years of teaching and administrative experience in higher education. He has functioned in many capacities including the role of Chief Information Officer of a university in North Carolina. His educational background includes BS degree in Medical Records Science, MS in Mathematics, MS in Computer Science, and a PhD in Industrial Engineering. He also has 18 graduate credits in Educational Research, Measurement and Evaluation. Dr Balogun's research interests are in intelligent systems design, decision aiding tools design, usability, and human computer interaction.