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PERFORMANCE MANAGEMENT OF DESIGN SUBCONTRACTORS BY USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

In aerospace industry, aircraft safety is ensured by aviation regulations while satisfying Design Organization requirements with Design Assurance System (DAS). Selecting subcontractor with low level capability can reduce airworthiness of aircraft which may ends up with cancellation of type certificate. The motivation of this study is the need to reply this capability evaluation gap in a flexible way. The aim of this paper is to evaluate performance of design subcontractors by multi-criteria evaluation, AHP, according to Key Performance Indices (KPI) generated from EASA Part 21 Design Organization Approval (DOA) requirements. Consequently, Artificial Neural Network (ANN) is applied to optimize the decision method of AHP.

INTRODUCTION

The purpose of this article is to purpose an indigenous way for subcontractor management. For subcontractor selection and evaluation, it is found that there is no realistic and realiable method. So this article tries to point this problem. Based on Aviation Authority expectations, DAS is composed of design, verification and monitoring functions to obtain the design organization as desired. Besides, satisfactory coordination of DOA holder with design subcontractor is the backbone to structure a capable design organization. [Zhang, 2014] To analyze this research study as a performance management tool, this method is divided in two major milestones and four minor steps. In first milestone, firstly, Delphi Method is applied with check list questionnaires as a survey to identify key DOA metrics. [Coetzee, 2008] Check list is used in design quality assurance audits covering EASA Part 21 DOA requirements. Questionnaires are applied to DOA and Airworthiness experts. As filtered check list questions bring out the main DOA subjects, these subjects are transferred into KPI. Secondly, AHP analysis is applied which helps to prioritize categories and subcategories relatively. Thirdly, KPI of each category is calculated with raw data and intervals of raw data are classified in six zones between 0 and 100. In this study basics of Annex IR EASA Part 21 and ISO 9001:2015 are used to identify KPI metrics. In the fourth step, coefficients calculated in AHP analysis are multiplied with of KPI grades. Finally, summation of each category generates the final grade of the subcontractor. To explain the meaning of final grade, five zones are introduced as a performance management dashboard. In the second milestone, AHP coefficients are ran into a special artificial intelligence tool, ANN, as a decision maker which will be described in detail in the third chapter of this paper.Raw data in this method implementation is generated from an aerospace company who works as design subcontractor of another DOA holder company. Besides, the selected company has an advantage in replying quickly changing industrial expectations with its design organization. The organization has an experience in aircraft development process over ten years.

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METHOD

I. Subcontractor Performance Index Board (SPIB)

In this study, SPIB is classified in five lines. After acquiring final grade by AHP analysis, performance of the design subcontractor is put in "**Subcontractor Performance Index Board".**

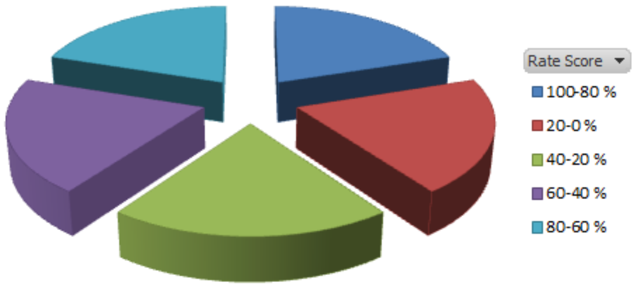

Figure 1 Subcontractor Performance Index Board (SPIB)

According to the figure;

- **0-20 %** range represents "**Insufficient**" region that is the bottom line in grade index. If subcontractor is in this range, it means that design development activities are not sufficient for contractor requirements and this subcontractor does not have systematic quality assurance system to fulfill EASA Part 21 requirements. Besides, a subcontractor in this zone carries a potential risk for airworthiness and safety of aircraft. Thus, it is not advised to delegate technical signatories to subcontractor.
- **40-20 %** range represents "**Weak**" region that is the second lowest line in grade index. If subcontractor is in this range, it means that design development activities needs to be improved to meet expectations such as restructuring design assurance system, outsourcing quality management consultant to focus on systems engineering processes. With this result, it is advised to monitor and re-run process delivery performance with new real time data to delegate technical signatories.
- **60-40 %** range represents "**Sufficient**" region that is the middle part of grade index. If subcontractor is in this range, basics of DOA activities are carried in operational basis. To improve traceability of DOA issues, categories and sub-categories of AHP method shall be reengineered. So, it is advised to delegate second level technical signatories that are not safety critical and airworthy.
- **80-60 %** range represents "**Strong**" region that is the second highest line in grade index. In this range, design subcontractor has sufficient competence in its design processes to meet contract requirements while satisfying EASA Part 21 requirements. However, subcontractor is lacking proactive steps to mature its Design Assurance System. As a result, it is advised to delegate some of first level technical signatories that effect airworthiness of aircraft.
- **100-80%** range represents "**Best Practice**" region that is the top line in grade index. In this range, subcontractor has superior in its competency level and it has ability to manage potential risks before it arises. So, it is advised that contractor can fully delegate its first level technical signatories because in this zone, contractor and subcontractor way of work are in line as partners. This level of maturity in subcontractor can lead to access full authority of related work packages.

II. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is an information processing technique that replicates the basic elements and mechanisms of the biological nervous systems. ANN learns and solves specific problems by mimicking the synaptic connections of neurons [Monteiro,2016]. ANN configures the net of artificial neurons (processing units) in the arrangement of three different intercommunicating layers. This multilayer processing system can be admitted as a black box where the essential features of neurons and their interconnections are simulated by a computational program. Feed-forward neural networks is the most common type that allow signals to travel one way only; from input to output. [Berkol, 2016] Since ANNs function well at identifying patterns or trends of data, they are well suited for classification, clustering and anomaly detection. **(Figure 2)** [Ghaed, 2017]

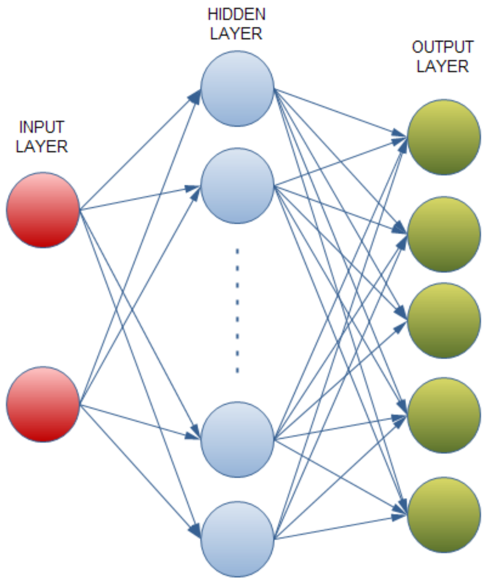

Figure 2 ANN Layer Model of SPIB

ANN is simply a mechanism of predicting the most accurate output by a function that maps the set of inputs as per their associated weights and influences on others. In the course of training, the weights are adjusted iteratively, refined continually by comparing the outputs with desired outputs. ANN learning algorithms can be classified as supervised and unsupervised learning. In supervised learning, data source provides the data sample with correct classification already designated and training is done for every input with corresponding target. On the other hand unsupervised learning algorithms identify hidden patterns in unlabeled input data. Here, learning algorithm is to find the structure and relationships among a few different inputs provided. Number of neurons is a measure of internal structure size and system's capability. Smaller structures may fail in accuracy whereas bigger structured networks are better to attain more complex solutions, even memorizing. Nevertheless, enormous internal structures bring the risk of slowing down the system, overfitting or may cause training to diverge.

III. Prioritization of Performance Metrics

In this research model, input parameters of AHP are divided in four main categories. Parameters related with DOA are identified with the guidance of Delphi Method. In first run of AHP, coefficients of these categories are calculated as given in below:

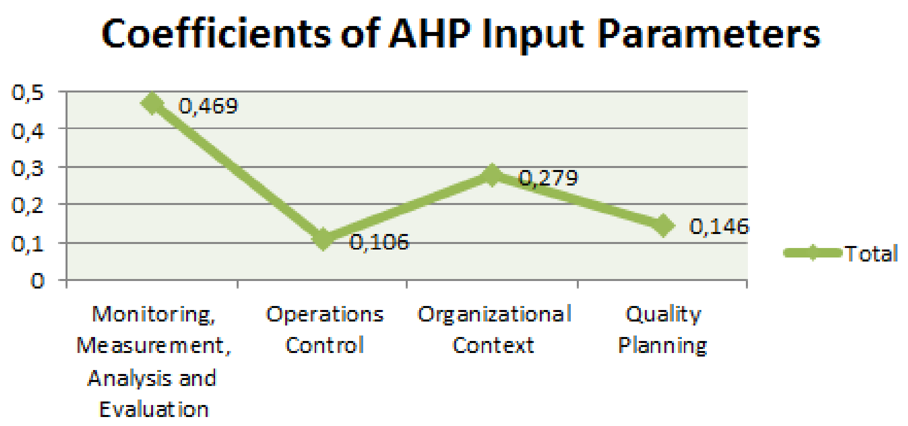

Figure 3 Coefficients of AHP Input Parameters

According to the figure above, the most important category is identified as "Monitoring, Measurement, Analysis and Evaluation". In the tables below, subcategories of are calculated as below:

Table 1 AHP Inputs of "Organisational Context"

Organisational Context	**AHP Results (ω)**
Quality Management Procedures	0,046
Scope of Organization	0,071
Signatory Turnover	0,029
Fulfillment of Customer Requirements	0,132
Quality Planning	**AHP Results (ω)**
Assignment of technical staff	0,015
Benefit Analysis	0,029
Lessons Learnt Performance	0,034
Organizational Knowledge	0,065
Operations Control	**AHP Results (ω)**
Design Review Effectivity	0,008
Design Changes	0,012
Nonconformity Ratio	0,016
Repetition of Nonconformity	0,025
Occurrence Reporting	0,042
Monitoring, Measurement, Analysis and Evaluation	**AHP Results (ω)**
Compliance to Annual Audit	0,058
Finding Management	0,053
Subcontractor Deliverable	0,058
Subcontractor Surveillance	0,129
Subcontractor Experience	0,170

After all of these sub-calculations are completed in AHP, identified rankings (0-5) are multiplied with the eigenvector of the related subcategory when the model is applied on raw data coming from design subcontractor. Then, the summation of sub categories is collected to obtain final value. In the second part, system is trained and tested by ANN. [Berkol, 2016] Below figure depicts the general system structure.

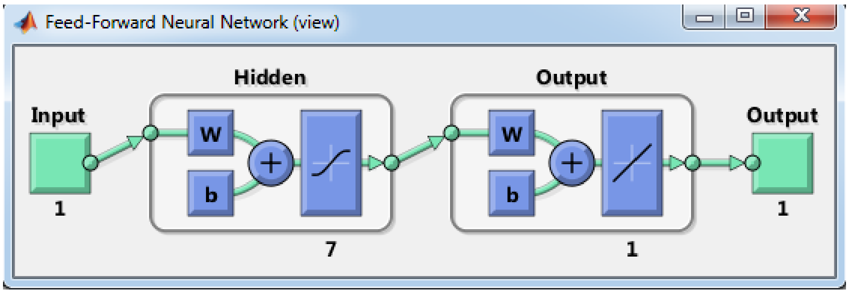

Figure 4 Feed-Forward Neural Network Structure

V. Conclusion

As explained in the introduction, the final grade of the design subcontractor is converted in 100-0 % scale index (Figure 1) of SPIB. In the case study, performance score is obtained as % 67 which is colored light blue and identified as "Strong" region for this aerospace company.

Table 2 shows the analysis parameters in tabulated form as follows:

Table 2 Parameters of Analysis

Parameter	Type
Training Function	Levenberg-Marquardt
Adaptation Learning Function	Gradient descent with momentum weight and bias learning function
Performance Function	Mean squared normalized error performance function
Number of Layers	2
Number of Hidden Layer Neurons	7
Minimum Gradient Value	5.94e-07
Transfer Function	Linear transfer function (purelin)
Data Division for Train/Test	Random
Total Iteration	148

This study's neural network architecture is feed-forward type back propagation training algorithm [Zacharis, 2016]. The system has an two inputs and one output. For training, Levenberg-Marquardt (LM) function is implemented since LM suits for training small and medium sized problems and yields better solutions with the refined parameters. On the account of best running time and accuracy, the number of layers is picked as 2 with 7 hidden layers in the analysis. In relation with the input/output numbers, the gradient value is set as 5.94e-07 being possible smallest value. To qualify the classification, Linear transfer function is selected. Refer to Figure 5 for Training state graphs and Figure 6 for Performance graph:

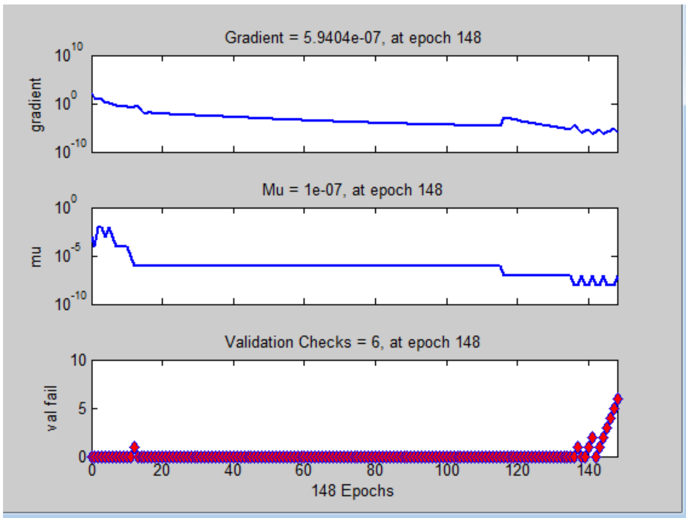

Figure 5 Training State Graphs for ANN

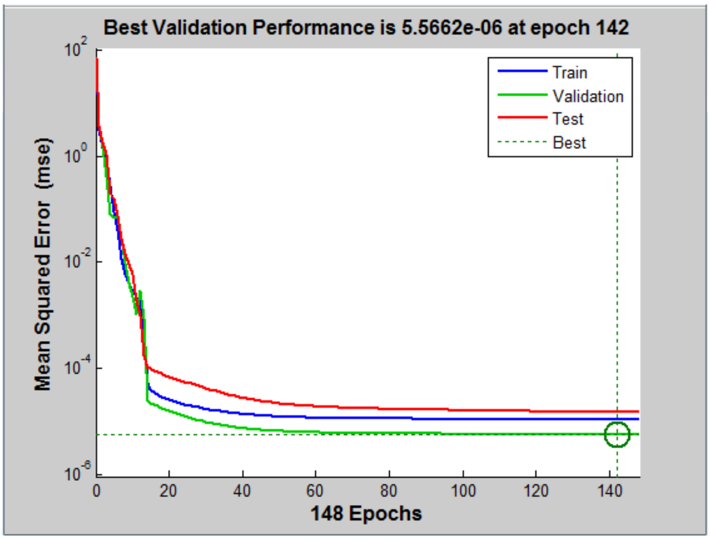

Figure 6 Performance Graph of ANN

VI. Future Study

This research study is generated to provide an exclusive tool for design subcontractor performance evaluation. Since DOA requirements that are referred in EASA Part 21 Subpart J are dependent on regulations, KPI metrics are open for further updates. Besides, since ANN method is preferred in this study, other types of classification techniques can be modified as ANFIS (Adaptive Neuro-Fuzzy Inference System), Support Vector Machines (SVM) etc. Also, for the bigger data applications, Deep Neural Network algorithms will be suitable for increasing the accuracy of the system.

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