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A Call for Generalized Aggregation Functions for Modelling Complex Decisions with a Mixture Categorical and Continuous Data

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This paper should be cited as follows:

Olagunju, A. (2018). **"A Call for Generalized Aggregation Functions for Modelling Complex Decisions with a Mixture Categorical and Continuous Data",** Athens: ATINER'S Conference Paper Series, No: **ELE2017-2600.**

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Tel: + 30 210 3634210 Fax: + 30 210 3634209 Email: info@atiner.gr URL: www.atiner.gr
URL Conference Papers Series: www.atiner.gr/papers.htm
Printed in Athens, Greece by the Athens Institute for Education and Research.
ISSN: 2241-2891
18/12/2018

A Call for Generalized Aggregation Functions for Modelling Complex Decisions with a Mixture Categorical and Continuous Data

Amos Olagunju

Abstract

Powerful aggregations functions are indispensable in the design and implementation of tree-based algorithms for use in making complex decisions. Boolean operators only support the complete presence or absence types of decisions and are insufficient for modelling complicated decisions. For instance, how will an engineer-hiring officer specify that a candidate who has earned the required critical engineering skill is the most preferred, next is the candidate with a related engineering skill, and last on list is the candidate who qualifies for skill training in engineering? Ideally, candidates with earned critical skills or related skills or require skill training should be assigned different scores. The personnel hiring officers require additional powerful operators for making effective intricate decisions with data from differently scaled categorical and continuous variables. The engineering officers should able to indicate strong conjunction, medium conjunction and conjunction, medium disjunction, and strong disjunction preferences; attach weights of importance to the decision criteria; and evaluate the qualifications of all candidates in order to compute the global cost-benefit ratings for each candidate. This paper presents cost and preference aggregation functions such as weighted arithmetic and geometric means, minimum and maximum functions. The endpoints of the series of aggregation functions, defined by a weighted power mean, are the logical conjunction and disjunction. A logic equation is usually derived by combining two or more elementary criteria using Boolean operators. Boolean interpretation is similarly provided to the aggregation functions in ways that Boolean interpretations are attributed to logic equations derived from elementary criteria scores. The paper presents the sensitivity analysis and the use of a logic scoring of preference and cost model to evaluate and select job applicants. The paper illustrates how the model is useful for making decisions with mixtures of categorical and continuous big data sets.

Keywords: Artificial Intelligence, Big Data, Decision-making.

Acknowledgments: The author gratefully acknowledges the insightful recommendations and suggestions of the reviewers of this paper. I am overwhelmed by the recommendations of the reviewers. I will continue to reflect on the positive suggestions of the reviewers in years ahead as we work on more Intelligence techniques.

Introduction

Engineering companies often develop a job advertisement and selection system to permit personnel officers to advertise new job openings, to allow prospective candidates to apply for any vacant job, and to enable personnel officers to review applications and manually fill openings based on job requirements and qualifications of the candidates.

Engineering personnel officers require quantifiable measures for providing the extent to which the candidates meet the requirements of specific jobs. This pertinent information would be useful to personnel officers in matching the "best" candidates to specific jobs. Quantitative evaluation of the degree to which the qualifications of candidates meet job requirements would provide objective evidence for the selection of the "best" candidates. This paper provides and applies a quantitative decision methodology for the evaluation and ranking of the candidates. Although the decision methodology is illustrated with the evaluation and selection of engineering personnel, the quantitative model is applicable to a variety of complicated decision problems (Dujmovic and Elnicki, 1981; Dujmovic, 1980; Information World, 1988; Salton et al., 1983; Su et al., 198la; b).

Decision Scenario

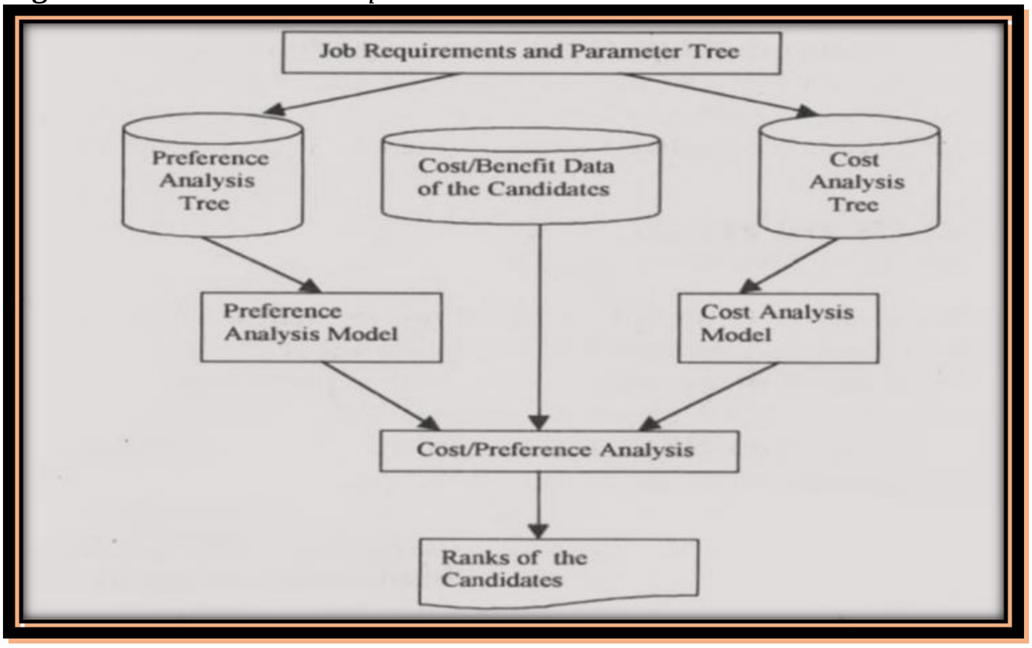
Given a list of enlisted candidates who applied for a job, the personnel officer wishes to fill the vacancy with the "best" candidate. Each candidate has provided a preference priority for the job. The personnel officer must evaluate the extent to which individual candidates meet the job requirements and then select the "best" candidate. Specifically, for each candidate, the personnel officer must evaluate the extent to which (1) the present pay grade matches the pay grade of the new job, and (2) the available date of candidate matches the job vacancy date. While trying to satisfy the job preference of the candidate, the personnel officer must minimize the cost of moving, first fill high priority requisition, and enforce all types of duty eligibility restrictions. Essentially, the personnel officer must weigh the costs and benefits of assigning the candidates to this job. Objectively, the personnel officer must rank order the candidates based on their overall ratings.

Decision Quantification

Herein the approach to decision making is predicated on a logic scoring of preference and cost model. The model uses the cost and preference trees and analytical algorithms to assess the suitability of the candidates for a job.

The generic job requirement and parameter tree in Figure 1 represents the personnel officer's specification of the requirements for a job. The job requirement and parameter tree contain both cost and preference parameters that are used to compute costs, and to evaluate preferences over several candidates. For conceptualization, the job requirement and parameter tree are split into a preference analysis tree and a cost analysis tree. These trees are used as input to a preference analysis model and a cost analysis model to compute a global cost-benefit score for each candidate. Note that the preference analysis tree and cost analysis tree need not be two separate trees. An extended continuous logic and a theory of complex criteria (Dujmovic, 1975) were used to perform cost and preference analyses and to compute a global cost-benefit score for each candidate. Specifically, the theory of complex criteria allows the evaluation criteria to be stated in explicit terms, whereas the logic permits the preference and cost to be expressed on a continuous scale between 0 and l instead of dichotomous rating (0 or 1).

Figure 1. *A Generic Job Requirements and Parameter Tree*



An elementary criterion is a mapping of the admissible values of a preference or cost parameter to real numbers in the range of zero to one. A set of elementary criteria must be formulated for preference and cost parameters that are leaf nodes of the job requirement and parameter tree in order to perform a preference or cost analysis. The elementary preference or cost E; represents the degree to which the assertive statement that "the value PV; completely satisfies the requirement of parameter P;" is true. Note that the candidates may provide the values of certain preference parameters but not their scores. There are several ways to formulate elementary criteria (Su et al., 198la). *Only* the approach useful for the evaluation and selection of candidates is introduced here.

Engineering personnel officers often use elements of logic informally in the evaluation and selection of the candidates. For example, consider the following decision on the skill classification eligibility (SCE) of different candidates. Suppose the job may or may not require skill classification (SCR). Furthermore, suppose a job that requires skill classification can be fulfilled by a training (SCT). The skill classification training can be satisfied by earning the critical skill classification (CSC) or a related skill classification (RSC) or qualification for skill classification training (QSCT). To qualify for SCT, the candidate must have 3+ in the number of skill classification's designated school (3PLUS) and 8+ in non-designated school credits (8PLUS). Formally, these eligibility decisions can be represented by the following logic equations:

QSCT = 3PLUS and 8PLUS;
SCT = CSC or RSC or QSCT;
SCE = SCR or SCT

Boolean operators "and/or" (Su et al., 198lb) are insufficient for adequately modelling complicated decisions because they *only* support complete presence or absence types of decisions. For example, how will a personnel officer specify that a candidate who has earned the required critical skill classification is the most preferred, next is the candidate with a related skill classification, and last on list is the candidate who qualifies for skill classification training? Ideally, each of the critical skill classification, related skill classification, and qualification for skill classification training should be assigned a different score. Given two criteria E_1, and E_2, a conjunction operator is used to specify a preference for both and a disjunction permits a preference for indicating either of them. To make complicated decisions, the personnel officer needs powerful operators for strong conjunction, medium conjunction, conjunction, medium disjunction, and strong disjunction. Moreover, the personnel officer should be able to attach weights of importance to decision criteria.

A major goal in the evaluation of the candidates is to compute the global cost-benefit rating, V, for each candidate, given some elementary costs and preferences and their relative weights. This goal can be achieved by making use of cost and preference aggregation functions such as weighted arithmetic and geometric means, minimum and maximum functions. Given the elementary criteria $E_1, E_2 \ldots E_n$ and their respective weights $W_1, W_2 \ldots W_n$, one powerful aggregation function is the weighted power series mean, V, defined as follows:

$$V = (\sum W_i (E_i)^r)^{1/r}, \text{ where sum is from 1 to n, } -\infty < r < +\infty, \text{ and } \sum W_i = 1$$

When n is two, Table 1 contains some of the more important functions.

Table 1. *Important Aggregation Functions*

Function Name	r	V
Maximum	$+\infty$	$Max(E_1, E_2)$
Square Mean	2	$(W_1 (E_1)^2 + W_2 (E_2)^2)^{1/2}$
Arithmetic Mean	1	$W_1 (E_1) + W_2 (E_2)$
Geometric Mean	0	$(E_1)^{W1} + (E_2)^{W2}$
Harmonic Mean	-1	$1/(W_1 (E_1) + W_2 (E_2))$
Minimum	$-\infty$	$Min(E_1, E_2)$

A logic equation is derived by combining two or more elementary criteria using Boolean operators and/or. When evaluated, a logic equation is either true or false. In the same way that Boolean interpretations can be attributed to logic equations derived from elementary criteria scores, Boolean interpretation can be ascribed to aggregation functions. For example, the logic conjunction corresponds to the minimum function Min (E_1, E_2 . . . E_n) and the logical disjunction operation corresponds to Max (E_1, E_2 . . . E_n). In spite of the fact that aggregated scored can be non-integral values, there is still the presence of conjunction and disjunction. The endpoints of the series of aggregation functions defined by the weighted power mean are the logical conjunction and disjunction. These series of aggregation functions are known as the generalized conjunction-disjunction. A variety of distinct generalized conjunction-disjunction functions can be constructed but only a few have been found useful in practice. In fact, our research shows that very few generalized conjunction-disjunction functions are required in quasi decision-making. Table 2 shows the six useful generalized conjunction-disjunction functions in the selection of candidates, and their associated values of r for selected number of elementary criteria (n) in a decision node.

Table 2. *Important Conjunctions and Disjunction Functions*

Function Name	**Operator**	**r(n = 2)**	**r(n = 3)**	**r(n = 4)**	**r(n = 5)**
Strong Quasi - Disjunction	D + +	20.63	24.32	27.13	29.29
Medium Quasi - Disjunction	D +	3.93	4.45	4.82	5.09
Weak Quasi - Disjunction	D -	1.45	1.52	1.56	1.59
Weak Quasi - Conjunction	C-	0.62	0.57	0.55	0.53
Medium Quasi - Conjunction	C+	-0.72	-0.73	-0.71	-0.67
Strong Quasi - Conjunction	C + +	-9.06	-7.64	-6.71	-6.10

The ranks of these functions and an aggregate function called the partial absorption function have been completely described in the literature. The generalized conjunction-disjunction functions must be carefully selected in any implementation to allow a distinction between preferences for dependent and independent existence of the characteristics of the candidates. Tables 3 and 4 contain the respective 17 and 25 levels of quasi disjunction and conjunction aggregation functions.

Table 3. *Seventeen Levels of Aggregation Functions*

Function Name	operator	Weight	1-Weight	r(n = 2)	r(n = 3)	r(n = 4)	r(n = 5)
Disjunction	D	0.0000	1.0000	inf+	inf+	inf+	inf+
Strong QD(+)	D++	0.0625	0.9375	20.63	24.32	27.13	29.29
Strong QD	D+	0.1250	0.8750	9.52	11.09	12.28	13.16
Strong QD(-)	D+-	0.1875	0.8125	5.8	6.67	7.32	7.79
Medium QD	DA	0.2500	0.7500	3.93	4.45	4.82	5.09
Weak QD(+)	D-+	0.3125	0.6875	2.79	3.11	3.32	3.45
Weak QD	D-	0.3750	0.6250	2.02	2.19	2.3	2.38
Square Mean	SQU	0.3768	0.6232	2.00	2.00	2.00	2.00
Weak QD(-)	D--	0.4375	0.5625	1.45	1.52	1.56	1.59
Arith. Mean	A	0.5000	0.5000	1.00	1.00	1.00	1.00
Weak QC(-)	C--	0.5625	0.4375	0.62	0.57	0.55	0.53
Weak QC	C--	0.6250	0.3750	0.26	0.200	0.17	0.16
Geo. Mean	GEO	0.6667	0.3333	0.00	0.00	0.00	0.00
Weak QC(+)	C-+	0.6875	0.3125	-0.15	-0.21	-0.22	-0.23
Medium QC	CA	0.7500	0.2500	-0.72	-0.73	-0.71	-0.67
Harmonic Mean	HAR	0.7726	0.2274	-1.00	-1.00	-1.00	-1.00
Strong QC(-)	C+-	0.8125	0.1875	-1.65	-1.55	-1.45	-1.36
Strong QC	C+	0.8750	0.1250	-3.51	-3.11	-2.82	-2.61
Strong QC(+)	C++	0.9375	0.0625	-9.06	-7.64	-6.71	-6.10
Conjunction	C	1.0000	0.0000	inf-	inf-	inf-	inf-

Table 4. *Twenty-five Levels of Aggregation Functions*

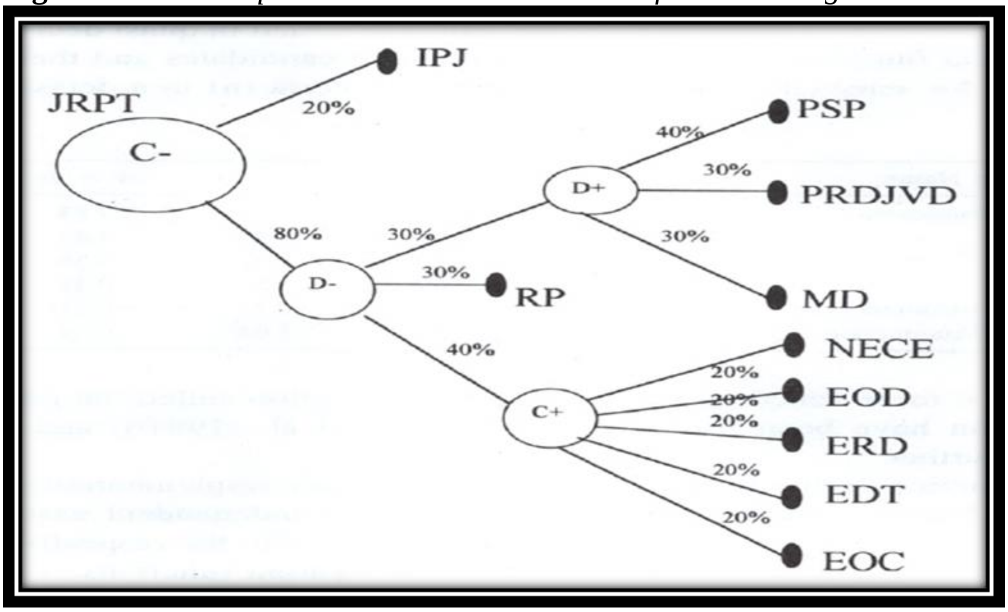
Function Name	Opera.	**Weight**	1-	r(n = 2)	r(n − 3)	r(n = 4)	r(n = 5)
Very Strong QD, Level 2	DV2	0.042	0.958	31.08	34.63	40.37	49.65
Very Strong QD, Level I	DVI	0.083	0.917	15.09	18.44	20.44	21.64
Strong QD, Level 3	DS3	0.125	0.875	9.52	11.09	12.28	13.16
	(D+)						
Strong QD, Level 2	DS2	0.167	0.833	6.70	7.82	8.60	9.15
Strong QD. Level I	OSI	0.208	0.792	5.02	5.81	6.35	6.71
Medium QD, Level 3	DM3	0.250	0.750	3.93	4.45	4.82	5.09
	(DA)						
Medium QD, Level 2	DM2	0.292	0.708	2.98	3.49	3.75	3.89
Medium QD, Level 1	DM·I	0.333	0.667	2.41	2.76	2.94	3.03
Weak QD, Level 3	DW3	0.375	0.625	2.02	2.19	2.30	2.38
	(D-)						
Weak QD, Level 2	DW2	0.416	0.583	1.62	1.72	1.79	1.83
Weak QD, Level I	DWI	0.458	0.542	1.29	1.34	1.36	1.38
Arithmetic Mean	ARI	0.500	0.500	1.00	1.00	1.00	1.00
Weak QC, Level I	CWI	0.542	0.458	0.75	0.71	0.69	0.68
Weak QC, Level 2	CW2	0.583	0.417	0.51	0.45	0.41	0.40

Weak QC, Level 3	CW3 (C-)	0.625	0.375	0.26	0.20	0.17	0.16
Medium QC, Level 1	CM I	0.667	0.333	0.00	0.00	0.00	0.00
	(GEO)						
Medium CQ, Level 2	CM2	0.708	0.292	-0.31	-0.36	-0.37	-0.37
Medium QC, Level 3	CM3	0.750	0.250	-0.72	-0.73	0.71	-0.67
	(CA)						
Strong QC, Level 1	CSI	0.792	0.208	- 1.28	- 1.24	- 1.16	-0.95
Strong QC, Level 2	CS2	0.833	0.167	-2. 12	- 1.94	- 1.77	- 1.59
Strong QC. Level 3	CS3	0.875	0.125	-3.5 1	-3. 11	-2.82	-2.6 1
	(C+)						
Very Strong QC. Level 1	CV l	0.917	0.083	-6.25	-5.51	-4.58	-3.41
Very Strong QC, Level 2	CV2	0.958	0.042	- 13.76	- 10.39	-9.68	-9.53

Illustration of Logic Scoring of Preference and Cost

The job requirement and parameter tree in Figure 2 is designed to illustrate the logic scoring of preference and cost technique, and to satisfy the decision scenario for the evaluation and selection of enlisted engineering candidates. The assumption implicit in the decision tree is, the lower the cost associated with the eligibility and preference the more suitable the candidate.

Figure 2. *A Job Requirement and Parameter Tree for Evaluating Candidates*



Here are the descriptions and strategies for measuring the values of the variables in the job requirement and parameter tree.

Individual Preference for Job (IPJ) Cost

It is assumed that several jobs are advertised as they become available. Each candidate can apply for a maximum of three jobs at a time. Moreover, each candidate indicates the preference for each job. Table 5 shows a scheme for associating a normalized score with the individual preference indicated for a job by each candidate.

Table 5. *Raw Cost and Normalized Score for IPJ*

Raw Cost	Normalized Score
0 if assigned to the first preference	0.00
1 if assigned to the second preference	0.33
2 if assigned to the third preference	0.67
3 if no preference is satisfied	1.00

Pay Grade Substitution Policy (PSP) Cost

Ideally, the pay grade of a candidate should equal the job pay grade if no cost is involved. Thus, the substitution of higher and lower pay grades have negative cost consequences, and should be minimized. Table 6 presents a method for assigning a normalized score to a substituted pay grade.

Table 6. *Raw Cost and Normalized Score for PSP*

Raw PSP	Normalized PSP
0 if job and person's pay grades are equal	0
1 if job pay grade is one up than person's pay grade	0.5
2 if person's pay grade is down or up 2 or more than the job pay grade	1.0

PRD and Job Vacancy Date (PRDJVD) Cost

Let (Y_1, M_1) and (Y_2, M_2) be the respective pairs of year and month for the projected rotation date (PRD) and job vacancy date (JVD) of the candidate. The following equations are used to compute the raw cost and normalized score of the projected rotation date and job vacancy date.

Raw PRDJVD Cost = 12(Y2 - Y1) + (M2 - M1 - 1)
Normalized PRDJVD = 0.2(Raw PRDJVD) for up to 5 months.

Moving Distance (MD) Cost

The moving distance is the distance between the job location and the current location of the candidate. One algorithm for computing the moving distance cost and normalizing its score is as follows. Table 7 is a sample of the raw cost and normalized score of the moving distance.

Compute Raw Cost = Integer part (($MD^{1/2}$)/7.5) and
Normalized Score = Raw Score/14 if MD is less than 110,244 miles and 1 otherwise.

Table 7. *Raw Cost and Normalized Score for MD*

Raw Cost	**Normalized Score**
0 if 0 to 56 miles	0
1 if 57 to **224 miles**	0.07
: : :	:
13 if 9,507 to **110,244 miles**	0.93
14 **if over** 110,244 miles	1.00

Requisition Priority (RP) Cost

It is assumed that high priority job requisitions will be filled first. Here are two equations for calculating the raw cost and normalized score of the requisition priority.

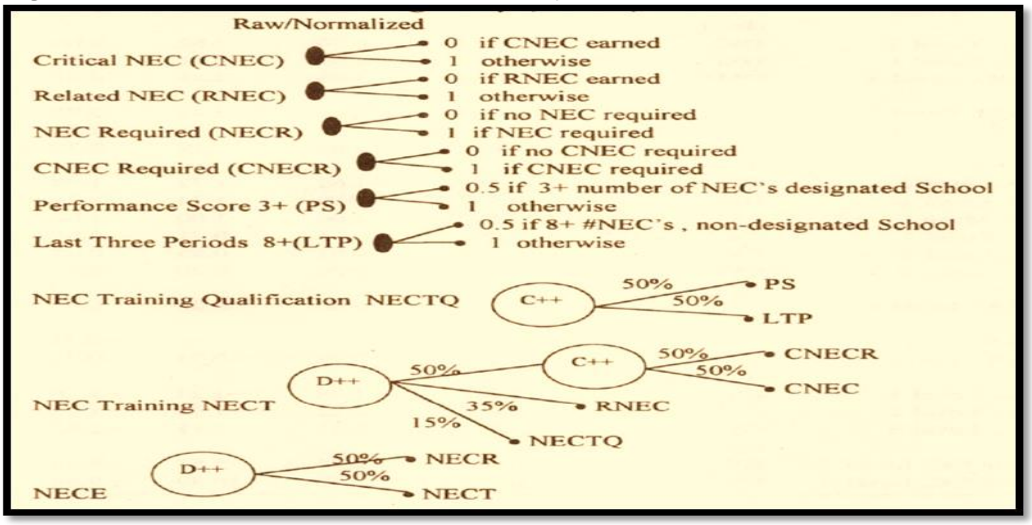
Raw RP Cost, RRP = $(RP)^{1/2}$, Normalized RP = l/RRP.

That is, we process high priority requisitions at low costs and low priority requisitions at high costs.

Candidate Skill Classification Eligibility (NECE) Cost

The computation of the skill classification eligibility for each candidate is complex. First, the normalized score of each critical, related, or required eligibility classification skill is set 0 or 1, depending on whether or not the skill is required, and the candidate has earned the skill. Second, the estimate of the normalized score attributable to the qualification for the skill classification training is derived. Third, the decision tree for each of (a) the skill eligibility classification training (NECTQ), (b) the skill eligibility classification (NECT), and (c) the candidate skill classification eligibility (NECE) is constructed with the appropriate conjunction and disjunction operators as shown in Figure 3.

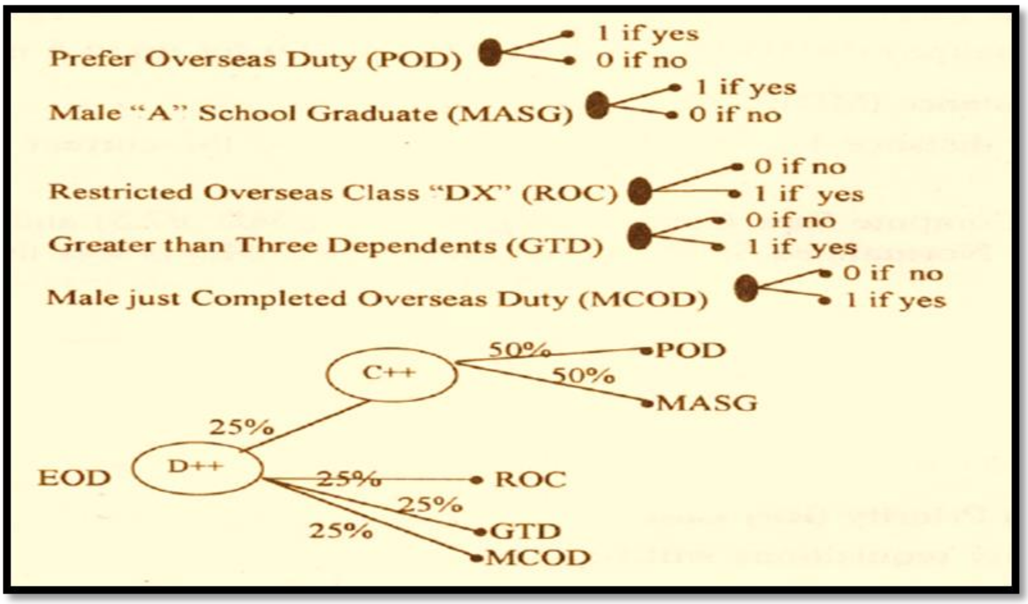
Figure 3. *Raw Cost and Normalized Score for NECE*



Eligibility for Overseas Duty (EOD) Cost

The decision tree for the evaluation of a candidate's eligibility for overseas duty is displayed in Figure 4. First, the normalized score each of the variables prefer overseas duty (POD), male a school graduate (MASG), restricted overseas classification duty (ROC), greater than three dependents (GTD) and male just completed overseas duty (MCOD) should be set to 1 or 0, depending on the status or preference of the candidate. Second, the decision tree for the evaluation of the eligibility of a candidate for overseas duty is created with the appropriate conjunction and disjunction operators as illustrated in Figure 4.

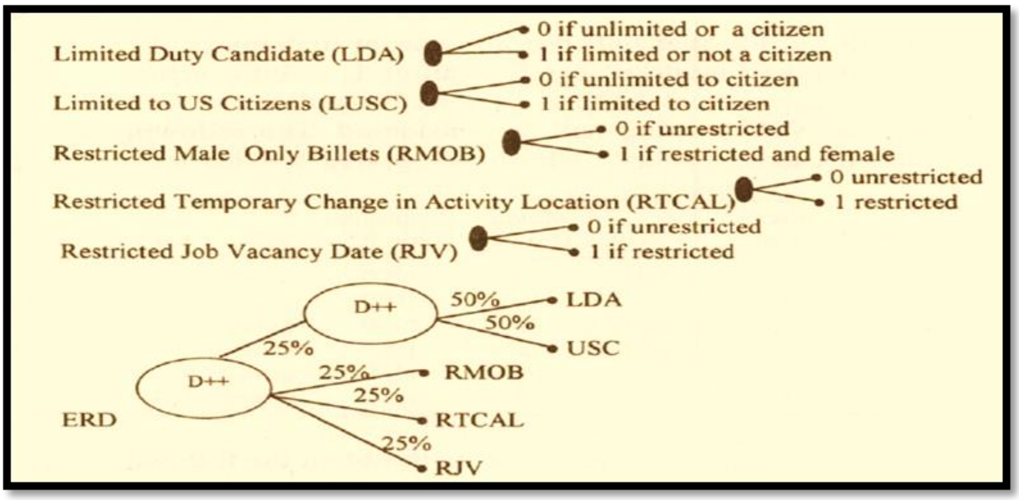
Figure 4. *Raw Cost and Normalized Score for EOD*



Eligibility Restrictions on Duty (ERD) Cost

Figure 5 reveals the decision tree for the evaluation of any restriction of a candidate for a job. First, the normalized score each of the variable limited duty candidate (LDA), job limited to US citizens (LUSC), male only duty candidates (RMOB), temporary restriction in change of duty location (RTCAL) and restricted job vacancy date (RJV) is set to 0 or 1, depending on the status of a job candidate. Second, the decision tree for the evaluation of the eligibility restrictions on duty for a candidate is constructed with the appropriate conjunction and disjunction operators as illustrated in Figure 5.

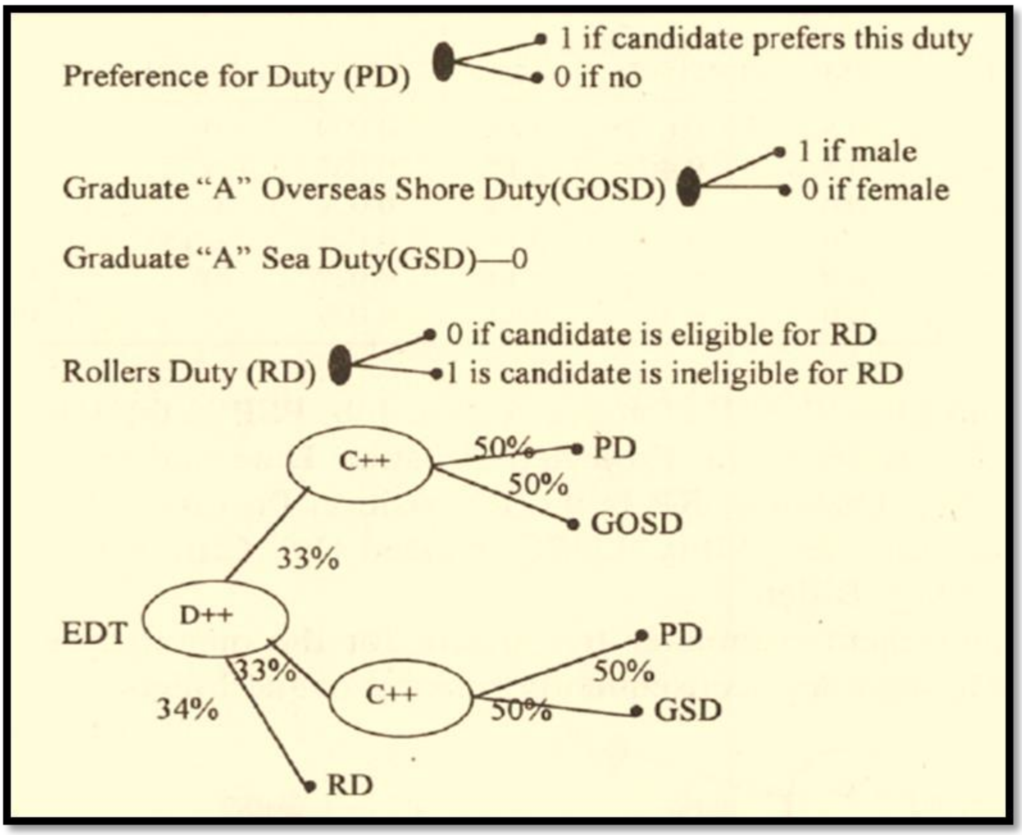
Figure 5. *Raw Cost and Normalized Score for ERD*



Eligibility for Duty Type (EDT) Cost

The decision tree for the evaluation of a candidate's eligibility for type of duty is exhibited in Figure 6. First, the normalized score of each of the variables prefer for duty (PD), graduate of overseas shore duty (GOSD), graduate of sea duty (GSD), and rollers duty (RD) should be set to 1 or 0, depending on the status or preference of the candidate. Second, the decision tree for the evaluation of the eligibility of a candidate for the type of duty is assembled using the appropriate conjunction and disjunction operators as shown in Figure 6.

Figure 6. *Raw Cost and Normalized Score for EDT*



Other Criteria Eligibility (OCE) Cost

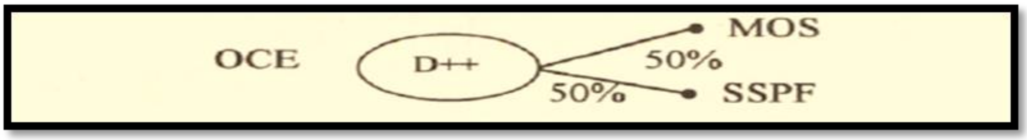
There might be other criteria eligibility such as, male only ship engineering duties and the enforcement of sea and shore duties for female candidates. Codes might be used to designate the types of sea and shore duties for female candidates as shown below.

Sea/Shore Policy for Females (SSPF) Cost

Raw SSPF	Normalized SSPF
0 if SSPF code is 2, 3, or 4	0.0
1 if SSPF code is 6	0.5
2 otherwise	1.0

When males apply for a male only shipping (MOS) job, there is no cost and all male applicants should be assigned zeros.

The decision tree for the evaluation of a candidate's eligibility for a job based on other set of criteria such as MOS and SSPF is as follows.



Evaluation Results

Consider an enlisted engineering job that will become vacant in January 2018. This male only sea duty with a pay grade of 4 job requires U.S. citizenship. Although an enlisted engineer with a critical combat skill eligibility classification (NEC) is preferred, candidates with related eligibility classifications or qualifications for skill eligibility classification training will be considered. Table 8 contains the profiles of six enlisted candidates who have applied for this combat engineering job. Note that IPJ is the preference of each candidate for the combat engineering job.

Table 8. *Profiles of Six Candidates for a Combat Engineering Job*

Candidate Number	*Pref. IPJ*	*Current Paygrade*	*Moving Distance*	*Req. Priority*	*NEC Citizenship*		*Gender*
111	0	3	500	1200	**earned**	U.S.	Male
222	1	3	450	1000	**related**	**U.S.**	**Male**
333	0	4	500	1200	**earned**	U.S.	Male
444	1	4	450	1000	**training**	U.S.	**Male**
555	0	4	500	1200	**earned**	U.S.	**Female**
666	0	4	600	1200	**earned**	U.S.	**Male**

This data is coded for quantitative decision, to obtain the normalized data in Table 9.

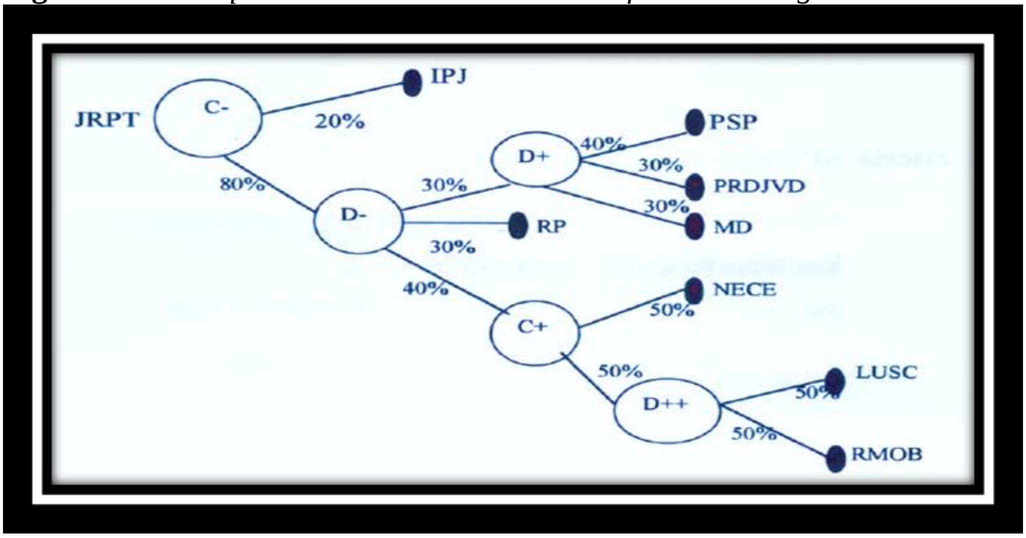
Table 9. *Normalized Data of Six Candidates for a Combat Engineering Job*

Candidat e Number	*IPJ*	*PSP*	*PRDJVD*	*MD*	*RP*	*NECE*	*LUSC*	*RMOC*
111	0.0	0.5	0.6	0. 14	0.029	0	0	0
222	0.3	0.5	0.4	0.14	0.031	0.35	0	0
333	0.0	0.0	0.6	0.14	0.029	0	0	0
444	0.3	0.0	0.6	0.14	0.031	0.15	0	0
555	0.0	0.0	0.4	0.14	0.029	0	0	1
666	0.0	0.0	0.4	0.21	0.029	0	0	0

Where IPJ is the Individual Preference for the Job, PSP is the pay grade substitution policy, PRDJVD is the projected rotation date and job vacancy date, MD is the moving distance, RP is the requisition priority, NECE is the skill engineering classification eligibility, LUSC is listed U.S. citizenship, and RMOC is required male only candidate.

One job requirement parameter tree useful for the quantitative evaluation of this normalized data, and consequently ranking of the candidates is shown in Figure 7.

Figure 7. *Job Requirement and Parameter Tree for Evaluating Candidates*



This tree was used in a quantitative data analysis of the six profiles of candidates for the combat engineering job in Table 9. The computed global costs and ranks for the candidates are displayed in Table 10.

Table 10. *Costs and Ranks of Six Candidates for a Combat Engineering Job*

Candidate Number	*Global Cost*	*Rank*
1 11	0. 16199	3
222	0.51734	5
333	0. 14614	2
444	0.32789	4
555	0.98656	6
666	0.09940	1

Discussion

The question naturally arises on the reliability of the newly developed quantitative decision methodology. A close examination of the results reveals that candidate 555 was placed last even though her profile is almost similar to that of candidate 666, but the job was earmarked for males only. The quantitative method detected this flaw. Note that candidates 444 and 222 were ranked 4 and 5 respectively. Each of these candidates rated this job as second priority, and each one of them required skill (NEC) training for this job. Candidate 111 required one-step up in pay grade and was positioned third place. The delay between the projected rotation date and job vacancy date received a somewhat higher penalty than moving distance, and consequently candidate 666 was ranked in front of candidate 333. It is reasonable to conclude that the decision model was reliable, given that it is responsive to sensitivity analysis. That is, the decision maker can alter the weights and/or quasi conjunction and disjunction operators to examine the effects of "what if" questions.

The comprehensive decision model in this paper has been applied to numerous Navy engineering personnel decision profiles in humongous databases for more than nine years. Consequently, for security reasons, the limited criteria of the comprehensive decision model are presented in this paper, to illustrate the usefulness of the model in the selection of competitive candidates. Nevertheless, the author is available as a specialist Fulbright scholar for consultations on numerous applications of the decision model in this paper. In fact, the practical implementation of the generalized methodology advocated in this paper exists in the literature (Olagunju and Tucker, 1989).

Applications of Decision Trees and Extended Continuous Logic

The identification of the risks posed by network systems is not easy. Effective risk assessments of systems require automatic self-auditing systems for collecting real-time data. There are laws that require healthcare and drug manufacturing companies to implement internal self-auditing computing devices for gathering compliance data that can be verified by external auditors. There are unintentional risks of errors and security due to the inexorable groundbreaking technological applications in medicine, the car manufacturing industry, electronic elections, and the management of complex organizations (Mercuri and Neumann, 2016). The never-ending reliance on the use of digital devices to monitor the health conditions of patients, who have no knowledge of imprecise meter displays, is a major problem design engineers and medical providers must resolve. Car manufacturing companies ought to be performing compliance testing for the standard verification of nitrogen oxide emissions by real road tests, instead of using automated factory test procedures. Certainly, reliable electronic systems should provide for external validation of all ballot entries. Unquestionably, the individual self-imposed monitoring systems of any complex organization, each with its implicit safety measures, can become catastrophic. The potential security risks in automated teller machines, global positioning systems, and electronic voting and monitoring systems can be evaluated with risk requirement trees and parameters. The decision scenario can be formulated in terms of the costs and benefits of various computing devices, implemented security measures and risk of exposure to various threats. The financial and consequential risks of each vulnerable computing device can be assessed with the method of logic scoring of preference and cost, and data analysis techniques presented in this paper.

Early prevention and detection of weak and malfunctioning hearts can undoubtedly help to reduce medical care costs. The risks of patients with varying heart rate characteristics are useful for estimating the likelihood of congestive heart failures. In fact, there are trustworthy algorithms for investigating the long-term variation in the features of heartbeat rates of patients with congestive heart failure, and for discriminating among patient's subject to low and high risk of congestive heart failure (Shahbazi and Asl, 2015). Clearly, the current paper presents the concepts of tree-based decision algorithms with logical scoring of heartbeat rates that would be valuable for discerning among patient's subject to low and high risk of congestive heart failure.

It is difficult to accurately forecast energy usage due to seasonal variations in the demand and supply of energy in regions around the world. Corporations ought to be able to balance the supply and demand for energy, in the presence of the shifting modern restorable energy resources, several weather conditions, and customer usage habits. Without a doubt, a neural network with backward propagation, the traditional support vector machine model, and a least-squares support vector machine for energy usage forecast have been reliably used to predict energy consumption (Yu et al., 2015). The normalized and weighted historical hourly energy used, humidity, temperature and wind speed over days were used as features to train and assess the effectiveness of each machine learning energy prediction model. Consequently, the tree-based decision algorithms proposed in this paper can benefit from the variety of available trustworthy algorithms for normalizing and assigning weights to different variables.

Consistent indicators of associations in massive datasets are essential for the design of intelligent data mining algorithms. The selection of correlations for the precise analysis of binary data from different problem areas require properties that: (a) guarantee the existence of relationship patterns beyond any doubt and make extremely related item sets noticeable in binary data investigations; (b) validate the accurate estimation of negative correlations; and (c) provide confidence about computed correlations, irrespective of any sample size increase (Duan et al., 2014). The advocated tree-based decision algorithms in this paper can be used to observe correlations in massive datasets by assigning weights that reflect the logically scored and organized items in the datasets.

Precise decision support systems are essential to the medical prevention, diagnosis, and treatment of diseases such as autism, cancer, celiac disease, and lobar pneumonia. There are medical decision support systems that apply the properties of fuzzy logic and neural networks to assist physicians to minimize medical errors have had limited success. The need exists to design and implement effective decision support systems for assisting physicians in curtailing medical errors. In fact, a taxonomy, techniques, and applications of fuzzy cognitive maps that are used in current medical decision support systems exist in the literature (Amirkhani et al., 2017). A fuzzy cognitive map is an uncertain directed graph for revealing the computational requirements and intricacies of a system. Fuzzy cognitive maps use a mixture of the topographies of neural networks and fuzzy logic to illuminate multifaceted systems. Precisely, to construct a fuzzy map, a user selects the total and category of model notions, defines the first model weight and the associations and connections among concepts, and uses learning procedures to train the early weight to attain the ultimate model. Similar to the decision methodology presented in this paper, the fuzzy cognitive map models and algorithms support reliable sensitivity analysis for discovering alternative solutions to a variety of many medical what-if questions.

Conclusions

This paper presents a quantitative hiring decision model for the objective evaluation and selection of engineering personnel. The approach to decision making is predicated on a logic scoring of preference and cost model. An engineering personnel officer specifies the requirements for a job and builds the cost and preference parameters of decision trees that are used to compute weighted costs, and to evaluate and rank candidates. Extended continuous logic and a theory of complex criteria were used to perform cost and preference analyses, and to compute a global cost-benefit score for each candidate. A decision model that supports sensitivity analysis and is reliable in enforcing the hiring policies and objectives of engineers is presented. The newly-developed quantitative model has been found useful in the evaluation and selection of military personnel for years. The newly developed quantitative decision methodology can be applied to personnel evaluation and selection in general; particularly in the Army, Airforce and Navy and Marine. The decision methodology can be used to consolidate a variety of huge data sets in data warehouses for reliable quantitative decision-making. The nature of the decision trees presented in this paper would be found useful in artificial intelligence applications that require data analysis of mixtures of categorical and continuous data.

The analysis, correlation and interpretation of big categorical and continuous data sets originating dynamically from multiple sources for real-world applications pose major challenges. Clearly, the big data sets from different application disciplines must be condensed and summarized into decision tress for making meaning decisions. This paper advocates a call for data large data sets to be summarized into meaningful categories of weighted decisions that reflect human decisions.

References

Amirkhani, A., Papageorgiou, E., Mohseni, A., and Mosavi M. 2017. A review of fuzzy cognitive maps in medicine. Computer Methods and Programs in Biomedicine 142(C): 129-145.

Duan, L., Street, W., Liu, Y., Xu, S., and Wu B. 2014. Selecting the right correlation measure for binary data. ACM Transactions on Knowledge Discovery from Data 9 (2): 1-28.

Dujmovic, J. J. 1975. Extended continuous logic and the theory of complex criteria. J. Univ. Bel grade. Ser. Math. 537: 197-216.

Dujmovic, J. J. 1980. Computer selection and criteria for computer performance Evaluation. International. J. Computer Inf. Sci. 9:435- 458.

Dujmovic, J. J., and Elnicki, R. 1981. An OMS Cost Benefit Decision Model: Mathematical models for data management system evaluation, comparison and selection. Special Report 2 (Part I), National Bureau of Standard PB 82-1770150.

Information World. 1988. Product comparison on contract management software. Information World. 21 November.

Mercuri R., and Neumann P. 2016. The risks of self-auditing systems. Communications of the ACM 59 (6): 22-25.

Olagunju, A. O., and Tucker, C. 1989. FORACLE: An expert decision support system for the evaluation and selection of alternative products. Proc. International Assoc. Modeling Simulation Tech. Enterprises 2: 131-140.

Salton, G., Fox, E. A., and Wu, H. 1983. Extended Boolean information retrieval. Comm. ACM 26: 1022-1036.

Shahbazi, F., and Asl, B. 2015. Generalized discriminant analysis for congestive heart failure risk assessment based on long-term heart rate variability. Computer Methods and Programs in Biomedicine 122 (2): 191-198.

Su, S. Y. W., Batory, D. S., Dujmovic, J. J., Elnicki, R., Navathe, S. B., Olagunju, A. O., and Parkers, J. 1981a. A DMS Cost/Benefit decision model: Cost and preference parameters. Special Report I, National Bureau of Standard. Contract N B80SBC0449, January. NTIS PB 82- l69566.

Su, S. Y. W., Batory, D. S., Navathe, S. B., Olagunju, A. O., and Parkers, J. 1981b. A DMS Cost Benefit Decision Model: Analysis. Comparison and Selection of DBMSs. Special Report 2 (Part II), National Bureau of Standard, Contract NB85BCA0499, July.

Yu, W., An, D., Griffith, D., Yang, Q., and Xu, G. 2015. Towards statistical modeling and machine learning based energy usage forecasting in smart grid. ACM SIGAPP Applied Computing Review 15 (1): 6-16.