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Personnel Selection for Software Requirement Engineering Tasks using Ontology and Fuzzy Analytic Hierarchy Process

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ABSTRACT

Selecting qualified personnel for any tasks within a multi-criteria environment is a complex process given that both qualitative and quantitative factors need to be evaluated simultaneously coupled with prevalent uncertainties and subjectivity. Several personal profile ontologies have been developed and deployed, but the information represented are static leaving out very important and dynamic properties of the personal data suitable for task handling in applications such as allocation of task during the software requirement engineering process. This work is aimed at providing an enhanced personal profile ontology that includes the dynamic properties of personal data for personnel selection. The enhanced personal profile ontology (e-PPO) is developed using protégé. The suitability of personnel's properties in this ontology for the software requirements engineering task allocation is further evaluated using the Fuzzy Analytic Hierarchy Process (FAHP) approach. Results obtained show that selecting the most qualified personnel for any software requirements engineering task can easily be obtained using multiple criteria from the enhanced personal profile ontology.

Keywords: Personal Profile Ontology, Personnel Selection, Software Requirements Engineering, Fuzzy Analytic Hierarchy Process

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1. INTRODUCTION

In our day-to-day businesses and endeavours, we are faced with occasions where we need to take decision and make choice among several alternatives. Decision making process is about selecting the most suitable alternative(s) according to certain criteria. This process is considered to be tough for decision makers because of its uncertainty and subjectivity (Bai and Chen, 2008; Lin, 2010).

This process therefore requires a systematic and logical approach in order to make the correct choice.

Personnel selection, a decision making activity, is the process of choosing candidates who have the qualifications required to perform a defined job. It determines the quality of personnel to be hired by the human resource management unit of any organization (Dursun and Karsak, 2010). Selecting personnel for any given task is a complex process because of the multicriteria nature and the presence of both qualitative and quantitative factors that need to be simultaneously evaluated in a decision making process (Alguliyev et al., 2015). Selecting the best alternative among several other alternatives is a multicriteria decision-making (MCDM) problem. MCDM is one of the most widely used decision making methods which is aimed at improving the quality of decisions making to be more explicit, rational and efficient (Deng et al., 2011; Noor-E-Alam et al., 2011). A typical MCDM problem involves a number of alternatives to be evaluated and a number of criteria to evaluate the alternatives. Example of such MCDM problem is selecting personnel for Software Requirement Engineering (SRE) tasks.

Selecting appropriate personnel with the requisite qualification and skills for SRE tasks becomes a major challenge considering the various components of the SR tasks and the uncertainties around diverse computing skills. Requirement engineering phase is one of the most essential phases in the software development process. It is the first phase of the software engineering process and it is a crucial factor which influences software product quality and productivity (Akpasam et al., 2019)

Guidelines requiring the development of any software product are specified in the software requirements (SR) phase of the Software Development Life Cycle (SDLC). The requirements for a system are the descriptions of what the system should do which reflect the needs of customers for a system that serves a certain purpose. The process of finding out, analyzing, documenting and checking these services as well as their constraints is called requirements engineering (RE) (Sommerville, 2011). Requirements are specified at the beginning of the development process and these requirements specifications are used as guidelines for the software development (Couto et al., 2014). IEEE Std 1233 (1998) defines requirement as a condition or a capability that must be met or possessed by a system to satisfy a contract, standard, specification, or other formally imposed document.

SRE provides the appropriate mechanism for understanding what the customer wants, analyzing need, assessing feasibility, negotiating a reasonable solution, specifying the solution unambiguously, validating the specification and managing the requirements as they are transformed into an operational system (Sommerville, 2011). Software requirement engineering is a well-defined process to identify stakeholders and their needs and also documents such requirements for proper system implementation (Mustafa et al., 2018). SRE is a sub-category of (RE) that deals with the elicitation, specification, and validation of requirements for software (Bourque and Dupuis, 2004) and it is critical for successful software development. RE has five phases: requirements elicitation, requirements analysis, requirements specification, requirements validation and requirements management (Hussein et al., 2021). SRE processes and activities are as outlined in Table 1.

Table 1: Software Requirement Engineering Processes and Activities

S/N	PROCESS	SUB-PROCESS	DESCRIPTION/ACTIVITES
1	Feasibility Study	Problem Analysis	• Assessing if the system is useful to the client • Stating the problem, problem domain and environment • Understanding the system behaviour and constraints in the system • Knowing the system inputs and outputs (from output of existing system)
2	Elicitation and Analysis	1. Requirement Discovery 2. Requirement Classification and organization 3. Requirement prioritization and negotiation	• Meeting with clients and stakeholders to capture and discover their requirement and needs • Users and customers ask questions about the system (scope, what they need, evolution etc.) • Identifying al sources of requirements • Identifying the software system's features • Finding out about the application domain, services to be provided, required performance, hardware constraints etc. (From documents describing the organization and work) • Organizing and describing the requirements • Ranking requirements (by stakeholders, customers and users) • Resolving priority conflict • Identification and analysis of risk associated with each requirement • Selecting appropriate requirements elicitation techniques
3	Specification	Elaboration	• Address issues such as representation, specification language, tools to use etc. • Produce Software Requirements Specification (SRS) Documents – should include natural language description, graphical models, scenarios • Developing a refined technical model of software functions and features together with their constraints using UML diagrams, Use Cases, Data Flow Diagrams, Entity Relationship Diagrams, analysis models etc.

S/N	PROCESS	SUB-PROCESS	DESCRIPTION/ACTIVITES
4	Validation	Review and Inspection	• Checking that the requirements define the system the stakeholders want by reviewing the SRS document and examines the specification • Checking for errors (omission, inconsistency, incorrect fact, ambiguity) in requirement specification and other factors affecting quality • Ensuring that work conforms to standards established for the process, project and product. • Carry out validation, consistency, completeness, realism checks as well as verifiability. • Adoption of some validation techniques such as requirement review, prototyping and test case generation.
5	Requirement Management	Planning	• Requirement identification • Management of changes in requirement • Tracing the relationship between each requirement and the system design (Traceability policies) • Knowing the tools for processing of requirement information • Managing relevant information and knowledge.

(**Sources**: Sommerville, 2011; Pressman and Maxim, 2014; Hussein et al., 2021)

The success of any software systems is measured by the degree to which the software system meets its intended purpose. SRE is the process of discovering the intended purpose (requirements) of any software system. Inappropriate collection of system requirements results in poorly defined system and user requirements which will eventually results in software project failure. Khan et al., (2014) stated that most software projects have not been successful; 31% of software projects are cancelled, 53% faces challenges while only 16% of software projects been successful. About 50% of all software projects fail because the final product does not meet the user expectations and demands. Several works pointing to ontology-based decision support system capable of automatically suggesting the best suited human resources for specific task have been done (Paredes-Valverde et al., 2018). For access to needed resources for effective decision support systems, they should be Sematic Web driven.

Semantic Web came with its important objective to provide Web information with a well-defined meaning that makes it understandable to both humans and computers (Paredes-Valverde, et al., 2018). Ontologies are the fundamental technology for modeling the domain information. Ontology, a formal and explicit specification of a shared conceptualization (Studer, Benjamin and Fensel, 1998; Usip and Ntekop, 2016), provides reusable and sharable knowledge with a formal and structured representation. Ontologies used for user profiling are mostly limited to taxonomies of user interests.

Other domain knowledge such as software development require the use of such technology for explicit specification. Decision making plays a vital role in real time applications where there are many decision criteria (Sona et al., 2018). Important decisions should be made by applying various quantitative methods MCDM such as Fuzzy Analytic Hierarchy Process (FAHP) (Prascevic and Prascevic, 2017). For modeling uncertainties in industrial, natural and human systems, fuzzy sets and fuzzy logic are powerful mathematical tools to adopt in order to facilitate decision-making as they use approximate reasoning and linguistic terms (Tavana et al., 2013). Analytic Hierarchy Process (AHP) was proposed by Thomas Saaty in 1980 as a multi-criteria decision method and has been applied in many domains, though it cannot perform well in an uncertain environment (Sona et al., 2018). In the traditional AHP method, the preparation of pair-wise comparison is a laborious process and its effectiveness is questionable (Szuts and Kromer, 2015). Its major advantage is its possibility to be combined with other methods including linear programming, fuzzy logic etc (Vaidya and Kumar, 2006).

Fuzzy logic is used to make conclusion that are based on uncertain, imprecise, vague and ambiguous information (Burney et al., 2017; Burney et al., 2018). Fuzzy AHP combines the methodologies of AHP and Fuzzy logic to solve multi-criteria decision making problems by capturing uncertain imprecise judgments of experts using linguistic variables to make the decision support system tolerant to imprecision and uncertainty (Saaty, 2008). FAHP is an efficient tool to handle the fuzziness of the data involved in deciding the preferences of different decision variables and pair-wise comparisons are done using fuzzy linguistic preference scale (Singh and Sharma, 2011). FAHP utilizes variables represented by triangular fuzzy numbers to perform pair-wise comparison among several alternatives (Kilincci and Onal, 2011).

The selection process is focused on personnel whose profiling has already been captured in the enhanced Personal Profile Ontology (e-PPO). The e-PPO is a variation of the existing Personal Profile Ontologies (PPO) which intends to capture the static and dynamic properties of the user and also the emerging uncertainties from some conflicting properties. Due to the uncertainties, fuzzy set theory remains the most common method to handle such decision making process (Cebi and Karal, 2017).

2. RELATED LITERATURE

Several studies have been carried out using different methods in order to objectively select personnel. Ontologies have also been used to model information in different domains. Usip and Ntekop, (2016) deployed ontology as an efficient and intelligent knowledge management tools for timetabling. Tiwari et al., (2018) and Mishra and Jain (2019) also adopted ontology as a secure semantic smart healthcare. The use of ontologies for user profile creation can be traced back to (Maria et al., (2007), with methods and applications carefully outlined. Requirements and knowledge engineering processes adopt the personal profile ontology in their reasoning (Sim and Brouse, 2014). Suárez-Figueroa, and Gómez-Pérez (2012) built ontology requirements specification, a reference ontology, to provide a consensual knowledge model of the employment domain to be used by public e-employment services. The application of ontologies has also been made in identifying requirements patterns in use cases (Couto, Ribeiro and Campos, 2014). An ontology-based approach was adopted in assigning human resources to software projects (Paredes-Valverde et al., 2018), but the work only covered the static personnel profile properties. This work is an enhancement as it looks at the dynamic properties in addition to the static properties.

Cebeci and Ruan (2007) developed an analytical tool for choosing the highest quality consultant that best provides customer satisfaction in a textile firm by identifying the most important criteria successfully using the fuzzy Analytic Hierarchy Process (AHP) to compare these consulting firms. Gungor et al., (2009) developed a personnel evaluation system based on fuzzy AHP by considering many quantitative and qualitative factors. Burney and Ali (2019) applied FAHP to select supplier in a textile industry in Pakistan; Sona et al., (2018) analyzed vendor selection problem in an automobile industry using FAHP and also choose their vendors, Cebi et al., (2017) evaluated students project and interpreted the results of the evaluation using FAHP; Nagpal et al. (2015) used fuzzy AHP to compare and rank different websites of an educational institute on their usability criteria. Chen et al. (2015) presented a framework for teaching performance evaluation based on fuzzy AHP and fuzzy comprehensive evaluation method. Jie (2010) applied fuzzy AHP to evaluate online course quality. Bruno et al. (2016) proposed a model based on the integration of AHP and fuzzy set theory for the supplier selection problem in a multi-stakeholder environment.

Dursun and Karsak (2010) proposed a fuzzy MCDM algorithm using the principles of fusion of fuzzy information, 2-tuple linguistic representation model and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Alguliyev et al., (2015) proposed a fuzzy hybrid MCDM model for personnel evaluation process. The objective was to determined evaluation criteria and evaluate personnel by means of VIsekriterijumska Optimizacija i KOmpromisno Resenje (VIKOR) in a fuzzy environment. Celik et al., (2009) combined fuzzy AHP with fuzzy TOPSIS to deal with the academic personnel selection problem. Keršuliene and Turskis (2014) developed a decision-making approach consisting of a combination of fuzzy weights, fuzzy AHP and triangular fuzzy numbers for an accounting chief selection in a firm. Due to the vague and imprecise ontology-based application information nowadays, as experienced in semantics-based applications information such as knowledge management, web-portals, etc., fuzzy ontologies have proven to provide enriched classical computational ontologies (Calegari and Ciucci, 2006). This work therefore combines the ontology-based and the FAHP approaches to select qualified personnel for SRE tasks.

3. MATERIALS AND METHODS

Personnel selection process requires the domain knowledge to be explicitly represented as well as clearly documenting the Software Requirements Engineering (SRE) task for personnel selection. This involves modeling the personal profile with both static and dynamic properties, obtaining the criteria required for the selection for any SRE task and their relative importance (weight).

3.1 The Enhanced Personal Profile Ontology (e-PPO)

Properties of the ontology such as name, gender, date of birth, etc. are static in nature and may not change. Other static properties such as educational qualification and skills acquired can be updated while others including area of specialization and profession are dynamic and can be changed. Also, areas of specializations cannot be out of the scope of one's profession, although one personnel can have multiple profession and skills, more than one profession can share things in common such as the same professional qualification may be required, and so on. Hence, Figure 1 shows the class hierarchy of the enhanced PPO with both static and dynamic properties of personal profile while Figure 2 gives an ontograf that shows excerpts from the PPO.

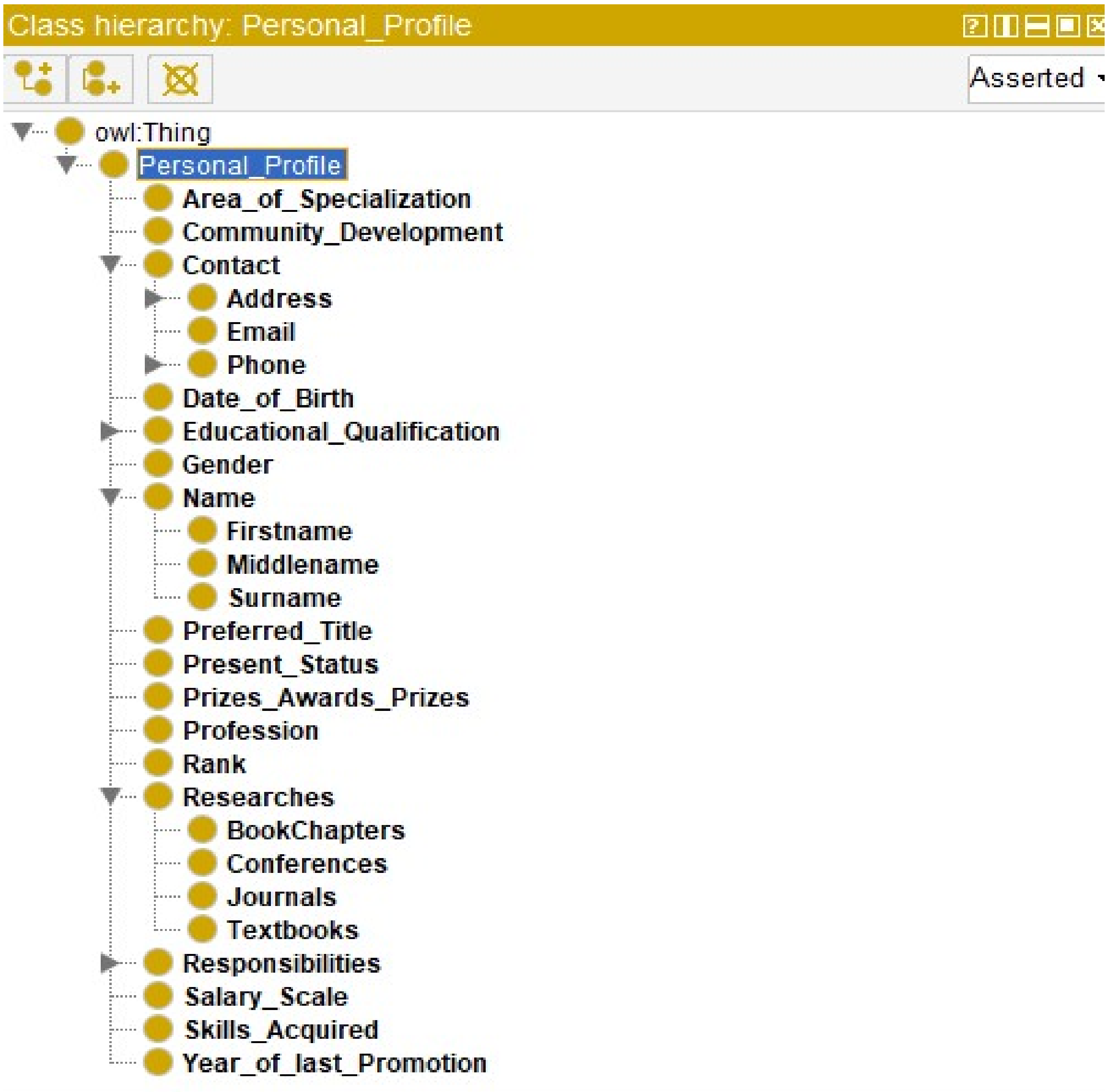

Figure 1: Class hierarchies in Enhanced Personal Profile Ontology

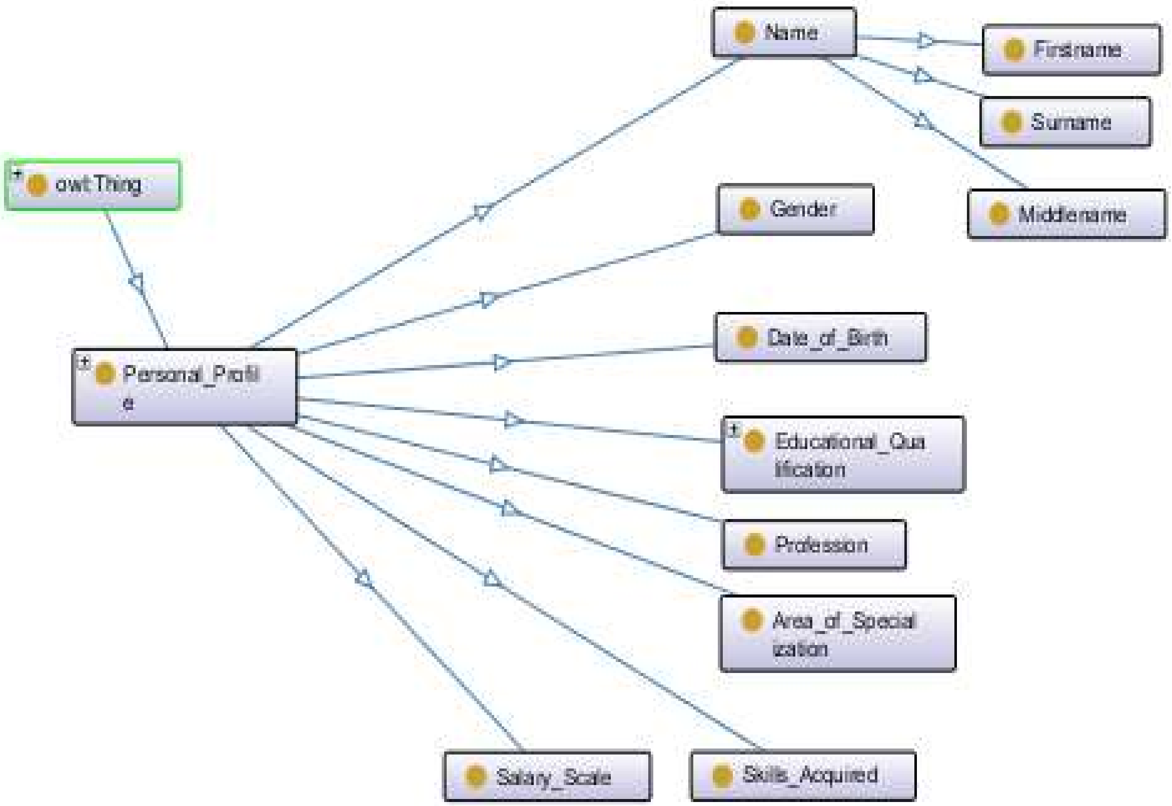

Figure 2: Excerpts from Enhanced Personal Profile Ontology

From this ontology, the software requirements engineering documents and the most qualified personnel can be formalized. Educational Qualification, Profession, Area of Specialization and Skills acquired are the most sensitive properties of the PPO with multiple criteria that introduces fizziness. Formalizing the ontology and the competencies of suitable personnel with varying properties for the SRE task demands additional evaluation of the multiple criteria using the fuzzy AHP evaluation approach.

3.2 The Weights of the Criteria used for the Evaluation

The criteria are weighted via linguistic expressions of relative importance. The weights of the criteria for the personnel selection are determined by the decision maker using the following linguistic variables: Absolutely Important (A.I), Strongly Important (S.I), Fairly Important (F.I), Weakly Important (W.I) and Rarely Important (R.I). The criteria used in the personnel selection process and the relative importance of each criteria and sub-criteria are shown in Table 2.

Table 2 - Relative Importance of Criteria and the Sub-Criteria

Criteria	Criteria label	Relative Importance	Sub-Criteria	Criteria label	Relative Importance
EDUCATIONAL QUALIFICATION	EDQ	A.I	Ph.D	Ph.D	F.I
			M.Sc	M.Sc	S.I
			B.Sc/HND	B.Sc/HND	A.I
			ND/NCE	ND/NCE	W.I
PROFESSION	PRO	S.I	Computer Science	CS	A.I
			Business Management	BM	F.I
			Information Technology	IT	S.I
AREAOF SPECIALIZATION	AOS	A.I	Software Engineering	SE	A.I
			Project Management	PM	F.I
			Management Information System	MIS	S.I
			Business/Data Analytics	BDA	F.I
			System Analysis	SA	A.I
			Information Technology Management/ Entrepreneurship	ITME	F.I
			Operations Management	OM	W.I
SKILL ACQUIRED	SKA	S.I	Knowledge Management	KM	A.I
			Quality Assurance/Engineering	QAE	F.I
			Data/Information Analysis	DIA	A.I
			Technical Writing	TW	S.I
			System Development/Testing	SDT	S.I
			Software Productivity Tools Usage	SPT	S.I
			Information Technology Risk Management	IRM	F.I

3.3 The Fuzzy Ontology based Personnel Selection System Architecture

Figure 3 shows the architecture of the fuzzy ontology-based intelligent system, where the formalized criteria obtained from the PPO is passed through a fuzzy AHP process to eliminate bias due to conflicting interest and intelligently select the most competent personnel for the SRE tasks.

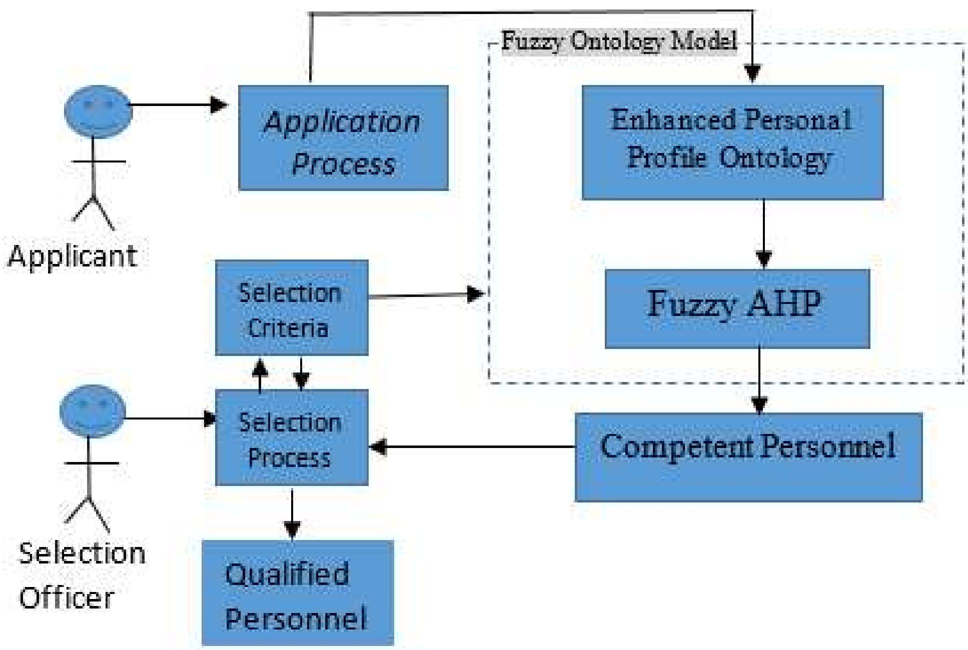

Figure 3: The Fuzzy Ontology based Personnel Selection System Architecture

From the architecture, the applicant completes the application process as input to the fuzzy ontology model, where the enhanced personal profile ontology is used with the fuzzy AHP rules to generate competent personnel. The selection officer views the competent personnel in the light of the organization's selection criteria to generate the most qualified personnel.

3.4 Fuzzy AHP Evaluation Approach

This study utilizes the method described by Buckley and uses triangular fuzzy membership function to calculate relative weights of criteria as well as alternatives. Reason for using triangular membership function is that all the approximate values for each criterion as described by the experts were around a single value instead of any standard or a range of values. In order to arrive at the selection of the best personnel for SRE tasks, identification of the criteria that impact the decision of the selection team is important. The hierarchy structure includes the goal, main criteria, sub-criteria and the alternatives as shown in Figure 4.

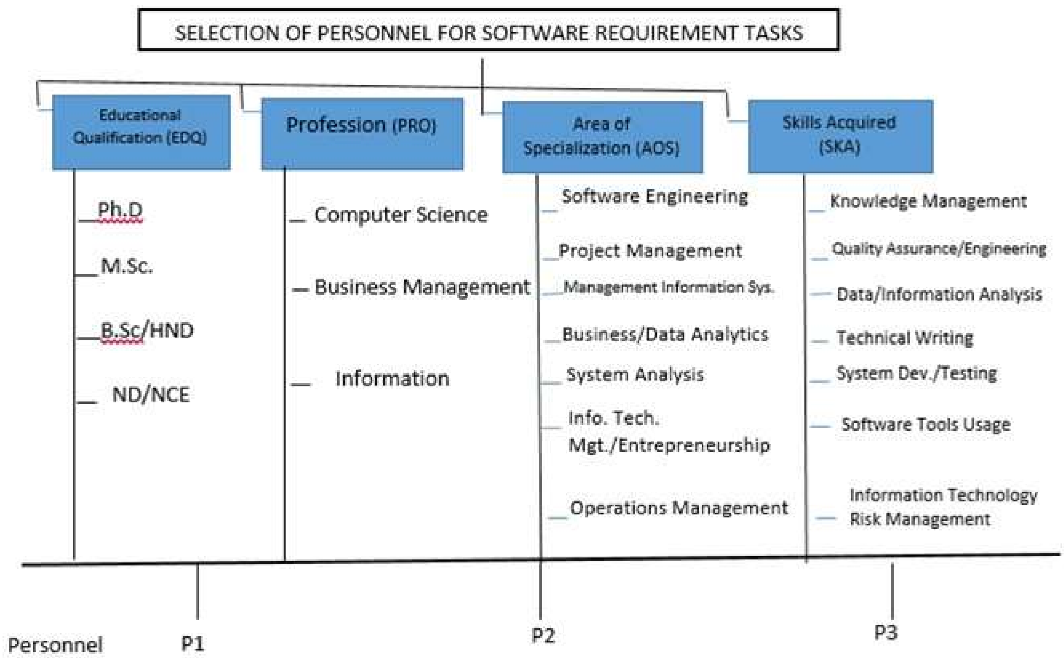

Figure 4: Hierarchy Structure for Personnel Selection

The steps highlighted below were followed to select the best personnel for SRE tasks:

Step 1 – Pair-wise comparison between criteria

The decision maker compares the criteria or alternatives using linguistic terms. The triangular fuzzy membership function in Figure 5 is defined by a lower limit a_{ij}, an upper limit b_{ij}, and a value m_{ij}, where $a_{ij} < m_{ij} < b_{ij}$

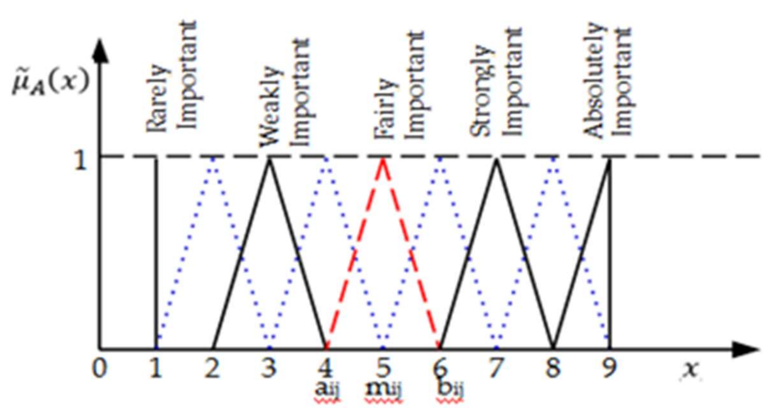

Figure 5: The Membership Functions of Triangular Fuzzy Numbers

The linguistic terms are mapped to the corresponding triangular fuzzy values in Table 3

Table 3 – Rule-based Linguistic Terms for the Linguistic Variables

	R.I	W.I	F.I	S.I	A.I
R.I	R.I	1/W.I	1/F.I	1/S.I	1/A.I
W.I	W.I	R.I	1/W.I	1/F.I	1/S.I
F.I	F.I	W.I	R.I	1/W.I	1/F.I
S.I	S.I	F.I	W.I	R.I	1/W.I
A.I	A.I	A.I	F.I	W.I	R.I

The pair-wise comparison matrix, making use of the linguistic terms rules in Table 3, for the criteria with respect to their linguistic variable: EDQ (A.I), PRO (S.I), AOS (A.I) and SKA (S.I) is depicted in Table 4.

Table 4 – Comparison Matrix for Criteria

	EDQ	PRO	AOS	SKA
EDQ	1	3	1	3
PRO	⅓	1	⅓	1
AOS	1	3	1	3
SKA	⅓	1	⅓	1

The linguistic terms in Table 4 are converted to membership functions. Equation (1) is used to convert the reciprocal fuzzy numbers to crisp values and displayed in Table 5.

$$\tilde{A}^{-1} = (l, m, u)^{-1} = (\frac{1}{u}, \frac{1}{m}, \frac{1}{l}) \qquad (1)$$

Where Ã is a fuzzy number, l is the lower point, m is the middle point and u is the upper point.

Table 5 - Fuzzified Pair-wise Comparison Matrix for Criteria

	EDQ	PRO	AOS	SKA
EDQ	1, 1, 1	2, 3, 4	1, 1, 1	2, 3, 4
PRO	¼ ,⅓, ½	1, 1, 1	¼ , ⅓, ½	1, 1, 1
AOS	1, 1, 1	2, 3, 4	1, 1, 1	2, 3, 4
SKA	¼ ,⅓, ½	1, 1, 1	¼ ,⅓, ½	1, 1, 1

Step 2 – Calculate the Fuzzy Geometric Mean Value

The geometric mean of fuzzy comparison values is calculated for each criterion using equation (2). This geometric mean was first proposed by Buckley in 1985.

$$\tilde{r}_i = (\prod_{i=1}^{n} x_{i,j})^{1/n} \qquad (2)$$

Where $\tilde{r}_i$ represents triangular numbers.

Two fuzzy numbers can be multiplied using the formular in equation (3)

$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1 * m_1 * u_1) \otimes (l_2 * m_2 * u_2) = (l_1 * l_2 ,\ m_1 * m_2 ,\ u_1 * u_2) \qquad (3)$$

Step 3 - Calculate the Fuzzy Weights

The vector summation of each $\tilde{r}_i$ is calculated; the reciprocal of summation vector, replacing the fuzzy triangular value in an increasing order is also calculated. The fuzzy weight ($\widetilde{w}_i$) of each criterion is calculated by multiplying each $\tilde{r}_i$ with this reverse vector. That is done using equation (4):

$$\widetilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1} \qquad (4)$$

Step 4 – Calculate the Weight

The weight of each criterion (w_i) is calculated by defuzzyfying triangular fuzzy numbers using the centre of area method (COA) as depicted in equation (5):

$$COA = w_i = \left(\frac{l + m + u}{3}\right) \quad (5)$$

Step 5 – Calculate the Normalized Weight

w_i is a non- fuzzy member and needs to be normalized using equation (6) to get a normalized weight (NW_i)

$$NWi = \frac{w_i}{\sum_i^n w_i} \quad (6)$$

4. RESULTS AND DISCUSSION

By applying equations 2 – 6 on Table 2, the results in Table 6 are gotten showing the normalized weights of the criteria.

Table 6 – Fuzzy Weights and Normalized Weights of the

	Fuzzy Weights ($\widetilde{w}_i$)	Weights (w_i)	Normalized Weight (NW_i)
EDQ	0.26, 0.38, 0.52	0.39	0.37
PRO	0.09, 0.13, 0.19	0.14	0.13
AOS	0.26, 0.38, 0.52	0.39	0.37
SKA	0.09, 0.13, 0.19	0.14	0.13

The normalized weights for the 4 sub-criteria with respect to Educational Qualification (EDQ), 3 sub-criteria with respect to Profession (PRO), 7 sub-criteria with respect to Area of Specialization (AOS) and 7 sub-criteria with respect to Skills Acquired (SKA) were calculated following steps 1 to 5 above. Table 7 shows the fuzzy weights and weights of the 21 sub-criteria.

Table 7 – Table Showing the Fuzzy weights of the Sub-criteria

CRITERIA	WEIGHT	SUB-CRITERIA	FUZZY WEIGHTS	WEIGHT
EDQ	0.37	Ph.D	0.08, 0.11, 0.18	0.12
		M.Sc	0.17, 0.26, 0.39	0.26
		B.Sc/HND	0.42, 0.58, 0.80	0.57
		ND/NCE	0.02, 0.05, 0.08	0.05
PRO	0.13	CS	0.43, 0.63, 0.83	0.62
		BM	0.15, 0.11, 0.14	0.13
		IT	0.17, 0.26, 0.35	0.25
AOS	0.37	SE	0.24, 0.24, 0.44	0.30
		PM	0.05, 0.14, 0.09	0.09
		MIS	0.77, 0.08, 0.17	0.11
		BDA	0.05, 0.14, 0.09	0.09
		SA	0.25, 0.24, 0.44	0.30
		ITME	0.05, 0.14, 0.09	0.09
		OM	0.02, 0.02, 0.03	0.02
SKA`	0.13	KM	0.19, 0.19, 0.42	0.25
		QAE	0.03, 0.19, 0.07	0.09
		DIA	0.19, 0.19, 0.42	0.25
		TW	0.08, 0.08, 0.17	0.10
		SDT	0.08, 0.08, 0.17	0.10
		SPT	0.08, 0.08, 0.17	0.10
		IRM	0.03, 0.19, 0.07	0.09

The weights and the fuzzy weights from Table 7 are used to calculate the priority weights of the Personnel with respect to sub-criteria of EDQ, PRO, AOS and SKA. Table 8 – 11 shows the calculated priority weights of the personnel.

Table 8 – Priority Weights of Personnel with respect to Sub-criteria of EDQ

Sub-Criteria	Ph.D	M.Sc	B.Sc/HND	ND/NCE	Priority Weight
Weights	0.12	0.26	0.57	0.05	
Personnel					
P_1	0.08	0.17	0.42	0.02	0.29
P_2	0.11	0.26	0.58	0.05	0.41
P_3	0.18	0.39	0.80	0.08	0.58

From table 8, the priority weight for the first personnel (P_1) is:

(0.12 x 0.08) + (0.26 x 0.17) + (0.57 x 0.42) + (0.05 x 0.02) = 0.0096 + 0.0442 + 0.2394 + 0.0010
= 0.29

The priority weight for the second personnel (P_2) is:

(0.12 x 0.11) + (0.26 x 0.26) + (0.57 x 0.58) + (0.05 x 0.05) = 0.0132 + 0.0676 + 0.3306 + 0.0025
= 0.41

The priority weight for the third personnel (P_3) is:

(0.12 x 0.18) + (0.26 x 0.39) + (0.57 x 0.80) + (0.05 x 0.08) = 0.0216 + 0.1014 + 0.4560 + 0.0040
= 0.58

This same approach is employed to calculate the priority weights of the personnel with respect to other sub-criteria.

Table 9 – Priority Weights of Personnel with respect to Sub-criteria of PRO

Sub-Criteria	CS	BM	IT	Priority Weight
Weights	0.62	0.13	0.25	
Personnel				
P_1	0.43	0.15	0.17	0.33
P_2	0.63	0.11	0.26	0.47
P_3	0.83	0.14	0.35	0.62

Table 10 – Priority Weights of Personnel with respect to Sub-criteria of AOS

Sub-Criteria	SE	PM	MIS	BDA	SA	ITME	OM	Priority Weight
Weights	0.30	0.09	0.11	0.09	0.30	0.09	0.02	
Personnel								
P_1	0.24	0.05	0.77	0.05	0.25	0.05	0.02	0.25
P_2	0.24	0.14	0.08	0.14	0.24	0.14	0.03	0.19
P_3	0.44	0.09	0.17	0.09	0.44	0.09	0.02	0.31

Table 11 – Priority Weights of Personnel with respect to Sub-criteria of SKA

Sub-Criteria	KM	QAE	DIA	TW	SDT	SPT	IRM	Priority Weight
Weights	0.25	0.09	0.25	0.10	0.10	0.10	0.09	
Personnel								
P_1	0.19	0.03	0.19	0.08	0.08	0.08	0.03	0.12
P_2	0.19	0.19	0.19	0.08	0.08	0.08	0.19	0.15
P_3	0.42	0.07	0.42	0.17	0.17	0.17	0.07	0.27

Finally, the aggregated result (Final Priority Weight) for each personnel according to each criteria and sub-criteria is calculated using the same approach. The result is displayed in Table 12.

Table 12 – Aggregation of Priority Weights of Personnel with respect to the Main Criteria

Sub-Criteria	EDQ	PRO	AOS	SKA	Final Priority Weight
Weights	0.37	0.13	0.37	0.13	
Personnel					
P_1	0.29	0.33	0.25	0.12	**0.26**
P_2	0.41	0.47	0.19	0.15	**0.30**
P_3	0.58	0.62	0.31	0.27	**0.45**

According to the final priority weight in Table 12, personnel P_3 is considered the best for the software requirement engineering task while personnel P_2 is the alternative choice.

The graph in Figure 6 gives the pictorial representation of the aggregated results that provides the final priority weight.

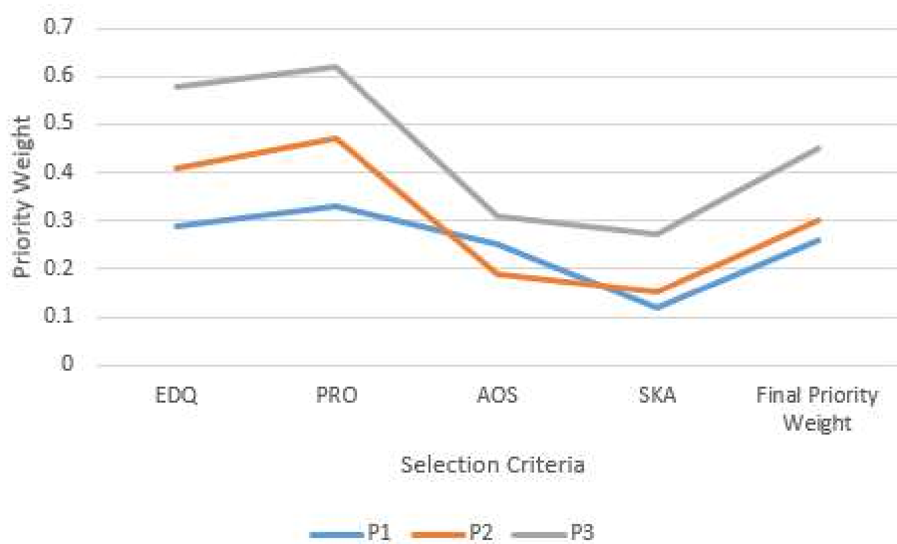

Figure 6: A plot showing the Final Priority Weight of Personnel against Selection criteria

From the graph, personnel P3 stands out in all aspects as the most competent when viewed criteria by criteria and even in the final priority weight. Personnel P2 on the other hand, seconds P3 but had the worst the area of specialization on comparing with Personnel P1.

5. CONCLUSIONS

Decision making process is about selecting the most suitable alternative(s) according to certain criteria. The enhanced personal profile ontology was created. Information represented in the ontology include static and dynamic properties of the personal profile suitable for task handling in applications such as promotion appraisal, and allocation of task during the software requirement engineering process. Selecting the most suitable alternative(s) according to certain criteria is sometimes considered to be a tough task for decision makers because of its uncertainty and subjectivity. The suitability of personnel's properties in this ontology for the software requirements engineering task allocation is further evaluated using the Fuzzy Analytic High Priority (Fuzzy AHP) approach. Results obtained show that selecting the most qualified personnel was possible. The final priority weight shows that personnel P_3 is considered the best for the software requirement engineering task while personnel P_2 is the alternative choice.

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