International Journal of Engineering & Technology, 7(4.16) (2018) 229-233

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper



Fuzzy-based Intelligent Shortlisting Process for Human Resource Job Recruitment Procedures

Caryl Charlene Escolar-Jimenez DBA[1], Kichie Matsuzaki PhD[2], Reggie C. Gustilo PhD[3*]

[1,2]Tokyo City University, Japan
[3]De La Salle University, Manila, Philippines
**Corresponding author E-mail: reggie.gustilo@dlsu.edu.ph*

Abstract

A fuzzy-based approach is used to simplify the process of shortlisting large number of job applications by systematically ranking individual applications primary according to their educational background, number of years of experience, and skill competencies that will match the employment position being offered. The proposed algorithm gives a full correlation of the applicant's qualifications and to the job requirement of the company. Three important outputs are delivered by this intelligent algorithm such as the naïve qualifier, job match and the final shortlist score. The naïve qualifier gives a score that balances the educational attainment and the numbe r of years of experience of the applicant. The job match score matches the competency or current job level of the applicant to the job level being offered. And lastly, the intelligent shortlist score which is the overall score that balances all the qualifications of an ap plicant such as educational attainment, years of experience and current job level. Results showed that the proposed algorithm can quantitatively analyze individual qualifications and rank the applicants effectively. The proposed algorithm will be used in the first stage of the recruitment process dealing with large number of applicants for shortlisting purposes

Keywords: *Fuzzy logic, intelligent algorithm, HR analytics, shortlisting, management.*

1. Introduction

Across all industries, organizations struggle to compete with cost, quality and innovation to remain competitive in a fast-paced changing world. The success of these organizations depend on the right people, strategically placed on the right positions armed with the right skills, knowledge and competencies. Identifying and managing human talent has become increasingly complex as it requires more resources and time to select the best candidate among numerous applicants. Studies highlighted that personnel recruitment and selection directly affects the quality of employees [1], therefore, deciding on the best candidate for the organization and the job begins in the crucial stage of recruitment and selection. The recruitment and selection process involves making decisions for the best fit candidate at the right time. Often, these may be very uncertain and difficult; as it depends on various factors such as human experience, knowledge, preference and judgement [2] by key decision makers in the organization and consequently guided by subjective opinions so there is no guarantee that the chosen candidate will be the actual best possible option for the employer [3]. The recruitment and selection procedure involves both the functional and human resources divisions to perform the evaluation mechanism, then group decision-making is used to avoid the biases of a decision-maker [4] towards the applicant. Generally, industries use a combination of selection methods based on their job nature, cost, time, accuracy, culture and acceptability [5]. The efficient use of ICT specifically as a strategic tool to advance and put resources into the correct innovations to engage and improve the profitability [6] is integral in HR as decision algorithms and classification technologies will streamline and optimize the HR recruitment and selection functions to minimize cost and maximize the competitive strength of the firm.

The planning part of the recruitment and selection phases determines the overall strategy and concrete measures to attract qualified employees [7] with the long-term goal of retention. As organizations have now evolved from a worker-severe industrial society to an automated information society, the labor force increasingly becomes more educated with higher competence and a decrease in loyalty [8]. Therefore, this study aims to utilize knowledge engineering techniques in the initial selection process to enable organizations to discover meaningful patterns and algorithms starting with the applicant data to shortlist candidates in an objective manner by matching organizational characteristics with the applicant's characters by clustering values that provides an applicant shortlisting result that are reflective to the specific needs of the firm.

2. Problem Statement

Due to the overwhelming number of applications received by firms for every job vacancy, the process of short listing qualified applicants becomes a dilemma for any human resource department especially coming from a large applicant pool with different skill sets and educational backgrounds. The usual manual selection procedure undergoes a subjective decision-making process that sometimes lead to hiring the least desired aspirant for the job. This research proposes an intelligent and systematic way of shortlisting job applicants who are good quality candidates at the first level of the recruitment process. A fuzzy inference system was utilized to make the algorithm very powerful in determining the proper ranking of job aspirants. This algorithm presents a naïve qualifier

Copyright © 2018 Authors. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

scoring system that was based only on the educational attainment and work experience of an applicant and was further processed with the job matching feature of this algorithm. Job matching was made to correlate with the competencies of the job aspirant and nature or position level being applied for. Overall, the proposed algorithm enables the human resource department to objectively shortlist the applicants according to the criteria of knowledge, experience and competency. The proposed algorithm gives three output parameters, the naïve qualifier, job matching and the intelligent shortlist score.

3. Design Process

The proposed intelligent shortlisting process was based on a fuzzy inference system that will determine the job applicant's fitness for the position. The overall systems design is shown in Figure 1.

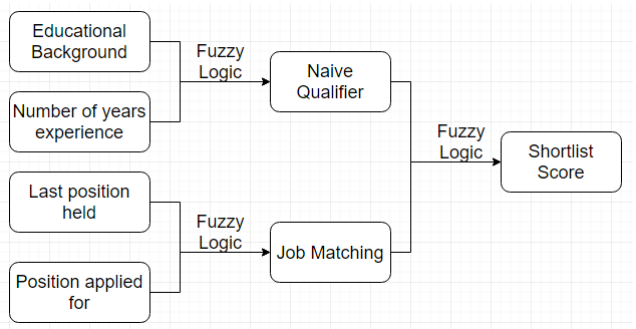

Fig. 1: Overall Systems Architecture

Figure 1 illustrated the overall systems architecture for the fuzzy-based intelligent shortlisting scoring and ranking system. It was divided into three parts and provided three outputs namely; the naïve qualifier score, the job matching score and the intelligent shortlist score. The naïve qualifier is a candidate scoring system that was purely based on the applicant's educational attainment and the number of years of experience. The job matching correlates the competency of the applicant to the job position being applying for and provides a better insight on the candidate's fitness to the job vacancy. Lastly, the balanced result of the naïve qualifier and the job matching produces an overall shortlist score for each individual applicant, therefore, becomes the basis for the final ranking of the applicant pool.

3.1. Naïve Qualifier

The naïve qualifier is a proposed method of acquiring the eligibility score of each applicant and to shortlist them according on the criteria of educational attainment and number of years of experience. A numerical representation of the eligibility of an applicant is the output of the naïve qualifier. Figure 2 showed the membership function for the educational attainment of each applicant.

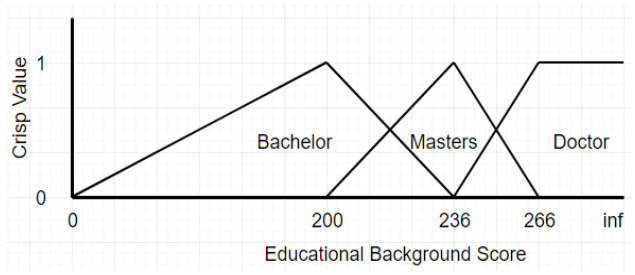

Fig. 2: Membership Function for Educational Attainment of the Applicant

Figure 2 exhibited the membership function for the educational attainment of the applicant wherein this provided a quantitative representation through the educational background score. The score was based on the acquired degree and the number of academic units earned by the applicant. A brief guide on the educational background score is shown in Table 1.

Table 1: Educational Background Scoring

Educational Attainment	Score	
	On-going	Graduate
Bachelor	Number of units (max of 199)	200
Masters	200 + number of units (max of 235)	236
Doctoral	236 + number of units (max of 265)	266 (also for post doctors)

Table 1 illustrated the computation of the educational background score by identifying the number of units earned by the applicant as this is vital in determining the correct score. An applicant with a bachelor's degree has a score of 200. Scores of 236 and 266 are applied to the graduates with a degree in the Master's level and doctoral level (and higher) respectively. The score can be increased if additional units are taken if the applicant pursues going to the next education level.

The next input for the naïve qualifier is the number of years of experience of the applicant and the membership function for this input is shown in Figure 3.

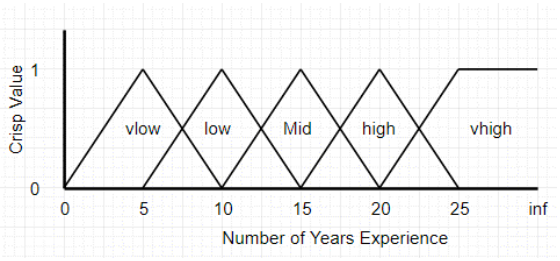

Fig. 3: Number of Years Membership Function

Fuzzy logic was applied to compute the naïve qualifier score. The following Fuzzy Associative matrix represented in Figure 4 was used as rules or performance indicators for the fuzzy inference system. The naïve qualifier score is the level of eligibility of the applicant and is purely based on the applicant's educational attainment and number of years of experience. The outputs used in this the fuzzy inference system are described as A= Superior, B= Excellent, C= Very Satisfactory, D=Good, E=Fair, F=Slightly Fair, and G= Poor. These indicators (A to G) were chosen to balance the educational background and the number of years of experience. This also considered the selection preference of some companies giving particular importance to work experience rather than the level of educational attainment of candidates or vice versa. In this case, the performance indicators in the fuzzy associative matrix in Figure 4 can be adjusted accordingly.

Years Experience \ Education	BS	MS	PHD
vlow	G	F	E
low	F	E	D
mid	D	D	C
high	C	C	B
vhigh	C	B	A

Fig. 4: Fuzzy Associative Matrix for Naïve Qualifier

3.2 Job Matching Level

The second output of the intelligent shortlisting process is the Job Matching. This is the competency level of the applicant relative to the job level available. The employment background, particularly the latest job level of the applicant is correlated to the level of

position applied for. The fuzzy membership function for the applicant's competency is shown in Figure 5

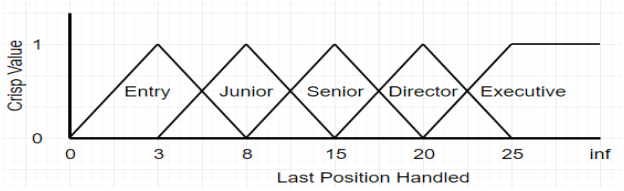

Fig. 5: Membership Function for Applicant's Competency

Meanwhile, Figure 5 considered the job position level but not the number of years of experience previously handled by the applicant prior to his application. These levels are similar to the management levels seen in most companies. An applicant with a score of 4 in the last position handled would indicate that he is currently on his first year in the junior level position. Whereas a score of 8 would imply that the applicant has spent 5 years or more in a junior level position. The computation of the fuzzy associative matrix for the job matching level is shown in Figure 6.

Applicant's Last Job Level

Offered Job Level	Entry	Junior	Senior	Dir	Exec
Entry	A	B	C	D	E
Junior	B	A	C	D	E
Senior	D	B	A	C	D
Dir	E	D	B	A	C
Exec	E	D	C	B	A

Fig. 6: Fuzzy Associative Matrix for Job Matching

Figure 6 illustrated the fuzzy associative matrix used in determining the correspondence between the applicant's latest job level in his previous company and the position level he is applying for. The letters in the fuzzy associative matrix means A= Strongly Matched, B= Moderately Matched, C= Matched to Some Extent, D= Poorly Matched, E= Worst matched. This technique demonstrated an efficient matching technique that gave the highest priority to applicants according to the same level of job positions and applicants who are currently one level below the offered job level while the least priority was allotted to those applicants coming from a level higher from the actual job offer. This also identified who will be given the lowest priority amongst all applicants who are at least two levels away from the offered job level.

3.3 Intelligent Shortlist Score

The intelligent shortlist score is the third and final output of the proposed algorithm. It is the result of combining the naïve qualifier score and the job matching score of the applicant. The intelligent shortlist score can then be used to rank the applicants while balancing their qualifications based on the criteria of educational attainment, number of years of experience and the matching level to the position applied for. Fuzzy logic is applied to the naïve qualifier score and the job matching score. Both inputs to this fuzzy logic has the same fuzzy membership function as shown in Figure 7.

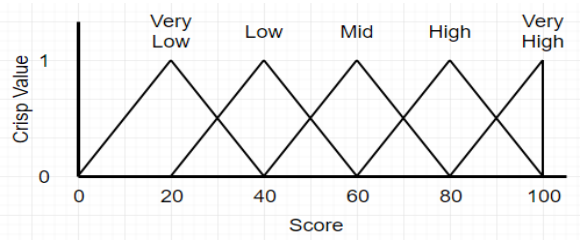

Fig. 7: Fuzzy Membership function for both the Naïve Qualifier and Job Matching Scores

Figure 7 indicated the fuzzy membership function used by both the naïve qualifier score and the job matching score. Both of these inputs have a score range from 0 to 100. The fuzzy associative matrix used to compute the shortlist score is illustrated in Figure 8.

Naive Qualifier

Job Match	vlow	low	mid	high	vhgh
vlow	I	H	G	F	E
low	H	G	F	E	D
mid	G	F	E	D	C
high	F	E	D	C	B
vhigh	E	D	C	B	A

Fig. 8: Fuzzy Associative Matrix for the Intelligent Shortlist Score

Figure 8 identified the fuzzy associative matrix used to compute the output for the intelligent shortlist score. The table indicated that there is a balance between the eligibility and competency of the applicant. This structure was chosen to give a better measure of the applicant's qualification and objectively measures the candidate's complementary skills and educational background.

4. Discussion of Results

To demonstrate the effectiveness of the Fuzzy-based intelligent shortlisting algorithm, a common ranking problem is presented. Five applicants with different educational attainments, work experience and current job levels were used to simulate the human resource recruitment and selection process. The profiles of the applicants are shown in Table 2.

Table 2: Profile of the Applicants

Applicant	Highest Educational Background	Number of years of work Experience	Last Job Position
A	Doctoral degree	10 years	Senior level for 7 years
B	Bachelor degree	20 years	Director for 2 years
C	Master's degree	5 years	Entry level for 3 years
D	Post-Doctoral degree	21 years	Executive for 2 years
E	Bachelor's degree with 12 units of Masters	18 years	Executive for 3 years

Table 2 showed a simple applicant profile but in reality, the number of applications received in a given company may increase significantly to more than 100 applicants during a given period and these high volume of applications leads to a time-consuming and often tedious shortlisting process. The current practice of recruitment and selection done by the human resource personnel is to manually evaluate each applicant that oftentimes lead to a subjective decision- making selection. The difficulty mainly lies in the balanced assessment in the criteria of educational attainment, work experience and competency of each applicant especially if two or more candidates have almost the same type of qualifications. The proposed algorithm gives an objective, fair and systematic shortlisting assessment for these types of job applicants. Using the output of the Naïve Qualifier, a ranking comparison of the profiles of the applicants is reflected in Table 3. The Naïve qualifier was able to balance the educational attainment and years of experience of the applicants in the proper scoring and ranking of the candidates. The result of the naïve qualifier was compared to three possible subjective processes, wherein the selection priority would either be assigned to the educational attainment

qualification, while another selection priority could favor the length of work experience qualification or the selection priority will consider the simple essential criteria where ranking is done based on the sum of all the ranks of the chosen criteria for evaluation.

Table 3: Applicant's ranking According to Qualifications

Applicants	Rank According to Education	Rank According to Years of Experience	Essential Effective Criteria		Rank Using Naïve Qualifier	
			Sum of Ranks	Final Rank	Score	Rank
A	2	4	6	2nd	55	4
B	5	3	8	3rd	70	2
C	3	5	8	3rd	25	5
D	1	1	2	1st	88	1
E	4	2	6	2nd	63.4	3

Table 4: Shortlist – From 5 Applicants to 3 Applicants

Applicants	Shortlist to Three Best Applicants								
	HR1	HR2	HR3	HR4	HR5	HR6	HR7	Essential Effective Criteria	Naïve Qualifier
A	4th	1st	4th	4th	4th	4th	4th	2nd	4th
B	2nd	3rd	2nd	2nd	3rd	3rd	1st	3rd	2nd
C	5th	4th	5th	5th	5th	5th	3rd	3rd	5th
D	3rd	2nd	1st	1st	1st	1st	5th	1st	1st
E	1st	5th	3rd	3rd	2nd	2nd	2nd	2nd	3rd

Table 5: Job Matching Results

Applicant	Current Job Level	Rank based on Position applied									
		Entry Level		Junior Level		Senior Level		Director Level		Executive Level	
		Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
A	Senior level for 7 years	60	2nd	60	2nd	100	1st	80	3rd	60	4th
B	Director for 2 years	52	3rd	52	3rd	84	2nd	88	1st	68	3rd
C	Entry level for 3 years	100	1st	80	1st	60	3rd	40	5th	20	5th
D	Executive for 2 years	32	4th	32	4th	52	4th	84	2nd	88	2nd
E	Executive for 3 years	28	5th	28	5th	48	5th	76	4th	92	1st

Table 6: Intelligent Shortlisting Results

Applicant Profiles	**Number of years of work Experience**	**Current Job Level**	**Rank based on Position applied**													
			Entry Level			**Junior Level**			**Senior Level**			**Director Level**			**Executive Level**		
			Naïve Qualifier	**Job Matching**	**Fuzzy Shortlist**	**Naïve Qualifier**	**Job Matching**	**Fuzzy Shortlist**	**Naïve Qualifier**	**Job Matching**	**Fuzzy Shortlist**	**Naïve Qualifier**	**Job Matching**	**Fuzzy Shortlist**	**Naïve Qualifier**	**Job Matching**	**Fuzzy Shortlist**
Doctoral degree	10 yrs	Senior level for 7 years	4th	2nd	**4th**	4th	2nd	**3rd**	4th	1st	**2nd**	4th	3rd	**4th**	4th	4th	**4th**
Bachelor degree	20 yrs	Director for 2 years	2nd	3rd	**2nd**	2nd	3rd	**1st**	2nd	2nd	**1st**	2nd	1st	**2nd**	2nd	3rd	**3rd**
Master's degree	5 yrs	Entry level for 3 years	5th	1st	**1st**	5th	1st	**4th**	5th	3rd	**5th**	5th	5th	**5th**	5th	5th	**5th**
Post-Doctoral degree	21 yrs	Executive for 2 years	1st	4th	**3rd**	1st	4th	**2nd**	1st	4th	**3rd**	1st	2nd	**1st**	1st	2nd	**1st**
Bachelor's degree with 12 units of Masters	18 yrs	Executive for 3 years	3rd	5th	**5th**	3rd	5th	**5th**	3rd	5th	**4th**	3rd	4th	**3rd**	3rd	1st	**2nd**

Table 3 signified that the naïve qualifier was able to rank the applicants' eligibility according to both the educational attainment and the length of work experience. This is in conjunction with the position of the subjective selection decisions that focused on either the educational attainment or the length of work experience of the candidate. This type of scenario holds true in the manual sorting of candidates in most organizations. Therefore, these similarities in the ranking score may lead to further subjective decisions by the human resource personnel that will be detrimental to the core competency of the organization in the long-term.

The relevance of the naïve qualifier is that it takes into account the exact scores that can effectively assess the candidates unlike the essential effective criteria wherein the scores are sometimes similar, as indicated by applicant A and E who were both ranked second, and applicant B and C who were both ranked 3rd. To further present the effectiveness of the proposed algorithm, 7 human resource personnel, the simple effective criteria and the naïve qualifier were used to shortlist the given 5 applicants down to the top 3 candidates. The results are shown in Table 4 below.

Results in Table 4 reflected that the naïve qualifier was consistent with the top 3 candidate decisions of the human resource personnel. However, upon further analysis, all of the 7 human resource personnel had different top 3 candidate decisions in the overall shortlisted applicants. Although, they had a very good understanding of the what is a best fit candidate for the job, the results still indicated the human aspect of being highly subjective in the evaluation criteria as this understanding is still not quantified formally based from the results shown in Table 4. Therefore, the naïve qualifier shortlisting function is to consolidate the different subjective ways of these human resource practitioners into a more objective, intelligent and systematic shortlisting feature.

In another aspect, an important parameter in the shortlisting of job applicants is the job matching function. There are times where applicants apply for high level job positions even if they have lower competencies and work experience. There may also be instances wherein some applicants currently handling top level positions may apply for lower level positions. These occur when applicants consider transferring to other companies due to reasons such as early retirement or company closures. Oftentimes, overqualified applicants become problematic for the company due to unreasonable demands such as higher compensation and other benefits once hired. The effectiveness of the job matching feature of the algorithm is shown in Table 5.

Table 5 simulated the sorting process of 5 applicants with different eligibilities and competencies applying for 5 different job levels. It can be seen that the job matching score can systematically sort the applicants according to the need or job level offered by the company. This job matching score helps the human resource personnel in selecting applicants that has the best fit to the position.

Eligibility and competency of an applicant are both important aspects in the selection criteria in choosing the best fit candidate for the right job. The proposed intelligent shortlist score evaluates applicants and balances the individual eligibility and competence by assigning a numerical score from 0 to 100. This scoring system may be used in sorting, and eventually shortlisting from a large applicant pool especially if most applicants have almost the same or equal qualifications. Table 6 showed how the proposed algorithm is able to systematically sort the applicants according to different job levels being applied for.

5. Conclusion

The proposed fuzzy-based intelligent shortlisting process streamlines and adds value to the recruitment and selection function with its ability to balance and coordinate organizational needs with the applicant's characteristics by providing a fair, objective and systematic way of evaluating the qualifications of job applicants according to their eligibility and competency. The three output scores of the algorithm, the naïve qualifier, job matching score and the intelligent shortlist score provides the human resource personnel the flexibility to adjust which selection parameter is preferred by the company. The proposed algorithm aims to help every HR department to systematically and objectively sort and shortlist a large number of job applicants effectively and efficiently as this reduces the time and resources needed in the selection process.

This algorithm is intended only for the first stage of the recruitment process to help identify and retain top talent in the long-term. The other stages of the recruitment process such as personality assessment tests, written examinations, job interviews, medical examinations and the like are not covered by the proposed algorithm.

References

[1] Chien, Chen-Fu; Chen, Li-Fei. "Data mining to improve personnel selection and enhance human capital: A case study in high-technology industry." Expert Systems with Applications, Vol. 34.1, pp. 280-290, 2008.

[2] Jantan, H., Hamdan, A. R., & Othman, Z. A. "Human talent prediction in HRM using C4. 5 classification algorithm." International Journal on Computer Science and Engineering, Vol. 2.8, pp.2526-2534, 2010.

[3] Kalugina, E., & Shvydun, S. "An effective personnel selection model." Procedia Computer Science, Vol. 31, pp. 1102-1106, 2014.

[4] Lin, H. T. "Personnel selection using analytic network process and fuzzy data envelopment analysis approaches." Computers & Industrial Engineering, Vol. 59. 4, pp. 937-944, 2010.

[5] Sivaram, N., & Ramar, K. "Applicability of clustering and classification algorithms for recruitment data mining." International Journal of Computer Applications, Vol. 4.5, pp. 23-28, 2010.

[6] Ahmadi, M., Malafe, N., & Baei, F. "Investigating the relationship between the use of ICT and human resource empowerment in Iran municipality (case study: Mazandaran province)." International Journal of Engineering & Technology, Vol. 7. 3.19, pp. 173-179, 2018.

[7] Frank, F., Tim, W., & Tobias, K. "An automated recommendation approach to selection in personnel recruitment." The Fifth Framework Programme Information Society Technologies, pp. 41-48, 2000

[8] Gadi, Dung P., & Hung, D. "Human resource management practices and turnover intention: the mediating role of perceived organizational support in tertiary institutions in Nigeria." Internation

[9] al Journal of Engineering & Technology, Vol. 7. 3.25, pp. 715-722, 2018.