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Betting on Yourself: A Decision Model for Human Resource Allocation Enriched With Self-Assessment of Soft Skills and Preferences

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ABSTRACT Recently, many approaches were proposed to support human resource management in finding the best human resources for available jobs. However, existing solutions do not effectively evaluate employees' skills, or they do only partially, neither provide mechanisms to describe subjects' skills and desiderata. To face this issue, this paper proposes a decision model for assisting human resource management in effectively evaluating the degree of mutual satisfaction in job-employee assignments. In particular, the decision model has been devised with the following core characteristics: i) employees' skills are modeled by combining hard skills (e.g.: academic training and competencies) and soft skills (e.g.: socio-relational experiences); ii) employees' soft skills are self-evaluated, giving importance not so much to experiences possessed but rather how such skills have been applied over time; iii) employees and managers can self-evaluate their preferences to enable the achievement of the optimal allocation by maximizing the global mutual satisfaction iv) partial matches between characteristics and desires of both employees and jobs are measured through a set of tailored fuzzy metrics. The proposed decision model has been validated in a real case to support the allocation of newly hired employees among open job positions in a Public Administration. Results showed an adequate ability of the proposed model both to support the description of employees, skills, jobs and preferences, and to suggest the best allocation maximizing the global mutual satisfaction. Summarizing, a decision model for human resource management with innovative characteristics is proposed and used to support decisions for a real allocation problem.

INDEX TERMS Human resource allocation, job search, recruiting, skills match, assignment problem, decision support, public administration.

I. INTRODUCTION

Public sector and companies have to continuously enhance their performance to survive the competitive market or budget cuts. This can be achieved not only focusing on improving technology, machinery, and software, but also on proper Human Resource (HR) management [1], [2].

One form of managing HRs is the process of employees allocation, for internal mobility or after hiring new employees. The goal of employees allocation is to get acquainted with jobs requirements and employees skills so that the right person can be selected for the right job. However, especially

in large organizations and in the public sector, it is increasingly difficult for HR managers to assign an employee to the right job since *i)* two tasks have to be solved together, i.e., each job position should be covered by the best employee available for that job, and each new employee should be allocated at the most compatible available position; *ii)* each employee possesses multiple skills and personal preferences, as well as each job has its intrinsic characteristics and some specific desiderata indicated by HR managers and, thus, it is becoming increasingly complicated to evaluate, manage, update, and memorize this information for all employees and jobs; *iii)* in order to obtain the best overall satisfaction for both HR managers and employees, some assignments may be sub-optimal [3], [4]. This problem is an example of the assignment

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problem [5], which is balanced in the case where the number of employees is equal to the number of open job positions. Different algorithms able to solve this type of problem exist (e.g., [6]).

As a consequence, more and more computerized tools and systems have been proposed to help managers in decision-making and employees allocation [7]–[10]. These tools can extend cognitive capabilities of managers helping them in managing and evaluating large amounts of data, and in finding the best employee for each available job [11]. However, existing solutions still fail to assign the right jobs to the employees according to their skills since the evaluation of the skills of employees is not a simple task, and several limitations have not been overcome yet.

Firstly, partial matches between jobs requirements and employees skills are not admitted or evaluated. Existing solutions typically offer to HR managers the chance to search for employees based on skills. Still, if someone only partially possesses the queried skills or at a different (lower or higher) level, they are excluded from the results. Besides, not all skills may be necessary, and some may be a preference of the HR manager, which could be handled as a bonus to reward candidates who have them. Managers should be allowed to express the preferred skills for a given job and view and evaluate candidates who do not entirely fit their preferences. Thus, a supporting system should offer a degree of fit between skills owned and required.

Secondly, assigning the best employee to a job is often not sufficient since employees tend to work poorly or inefficiently if their expectations and personal preferences are frustrated [10]. Existing solutions typically allow employees to describe their technical skills and expertise but more advanced criteria, such as social factors, personal preferences and career objectives are rarely considered. Therefore, in order to assess the goodness of each job-employee pair, the matching degree between characteristics and desires of both employees and jobs should be measured, taking into account different points of view; in particular, characteristics of jobs should relate both to the job activity and to professional prospects.

Thirdly, characteristics of employees should include both hard skills (e.g.: academic training, technical competencies and job experiences) and soft skills (e.g.: socio-relational experiences). Existing solutions mainly consider hard skills, not properly including employees' soft skills. This knowledge represents the social experience gained by each employee and certainly impacts how employees react to a job assignment. Every company or business organization should utilize the soft skills of employees to share knowledge and keep learning to improve the satisfaction and capability of employees [12].

Finally, to the best of our knowledge, none of the existing systems let managers and employees to self-evaluate how their expectations have to be weighted in the calculation of the optimal assignment. Personal preferences can substantially impact the mutual satisfaction of employees and managers

after a given allocation. Even if personal preferences are considered during the allocation process, individuals' perceptions can be very different. If the same metric is used for each individual, the generated allocation may be skewed by incorrect assumptions.

To face these issues, this paper proposes a decision model, based on Artificial Intelligence (AI) methodologies, for assisting HR management in effectively evaluating the degree of mutual satisfaction in job-employee assignments. The purpose of this model is to allow the HR management to acquire a more advanced awareness about the experiences, preferences, and unique characteristics of its personnel, and to promote an increasingly adequate meeting between them and the characteristics of the job activities to be carried out.

In particular, the decision model has been devised by integrating: *i*) descriptions of employees based on both their hard and soft skills and on their desires about their ideal job; *ii*) descriptions of job positions based on their intrinsic characteristics and on the desires of the managers about the ideal employ; *iii*) partial matches between characteristics and desires of both employees and jobs, measured through a set of specifically defined fuzzy distance metrics; *iv*) an efficient AI-based optimization algorithm to select the most satisfactory set of assignments. In particular, employees' soft skills are self-evaluated qualitatively on the basis of the frequency with which they occurred in job behaviors, in other words giving importance not so much to experiences possessed but rather how such skills have been applied over time. Moreover, employees and managers are also allowed to self-evaluate their preferences, weighting them by means of an approach based on tokens, in order to achieve the optimal allocation by maximizing the global mutual satisfaction.

The proposed model has been experimented and validated in a real case study at the Italian Ministry of Economy and Finance (MEF), with a number of new employees, hired through public competition, to be assigned to open job positions. The results has been presented as suggestions to the human in charge of the allocation, to save time and efforts associated with the full decision-making process. The comparison between suggestions and final decisions have been reported and discussed, to prove the efficiency of the proposed model.

The paper is organized as follows. Section 2 reports related work on HR allocation, describing different approaches and systems proposed in literature. Section 3 describes the proposed decision model. Section 4 presents the real case where the proposed framework has been applied. Then, Section 5 presents and discusses the results achieved, followed by conclusions in Section 6.

II. RELATED WORK

Employees skills, knowledge and competence highly impact the success of a job [3], [13]. However, getting the right employee to be assigned to the right job is not a trivial process, and, as a consequence, many approaches and

tools have been proposed to support HR managers in decision-making.

A. ALGORITHMS AND MODELS

The first algorithms and models appeared a couple of decades ago are based on evolutionary, genetic and simulated annealing techniques.

In more detail in [14] a multi-purpose evolutionary technique has been presented to optimize the expansion of competency sets by multiple criteria.

In [15] a genetic algorithm has been introduced for resource allocation of a software project including project activities and human resources available.

A hybrid model has been discussed in [16], based on multi-criteria decision making to assess the company's expertise.

In [17] a method based on the rough set theory has been outlined to explore high-performers' required competencies.

A constraint-based approach has been proposed in [18] for optimizing the scheduling of HR allocation with accelerated simulated annealing.

Successively, in the last decade, different techniques have been introduced to handle also inexact matches in HR allocation task as well as to allow the search for the right information and the reschedule of resources based on it.

In detail, an indexing technique has been proposed in [19] in order to retrieve the proximity of the keyword when exact match is not found. This technique is used to help managers in retrieving relevant information when exact match does not exist, and providing adequate resources to improve skill sets of the closest match selected.

A multi-objective algorithm has been proposed in [20] to minimize the cost during the scheduling process taking advantage of the knowledge to perform sequential search and to reassign and readjust the resources to respective tasks.

A decision model for dynamically scheduling software projects has been discussed in [21], based on employees skills which can improve over time as well as motivation and learning ability.

More recently, in [22] a model based on Formal concept analysis has been proposed in order to perform both skill extraction and skill matching of the projects to a team of students. The skill extraction involves both technical and non-technical skill extraction while for skill matching formal concept analysis and project-oriented stable marriage algorithm have been employed.

The decision model described in [23] has been devised with the aim of assisting a software company to evaluate existing resource for making decisions on whether the estimation of the tender is feasible, and assisting to make human resource allocation for team formation in fixed project duration with labor skill and budget constraint.

A combination of Fuzzy approaches with genetic algorithms has been proposed in [24] to handle uncertainty in subjective knowledge and evaluate the potential assignment of candidates to job vacancies based on their competency and the significance of each position.

In [25] a multifactor human performance evaluation approach based on the factor space theory has been designed. A fuzzy approach is used to not only evaluate the performance of candidates based on some criteria, but also provide some constructive criticism or suggestions for employees in professional and personal improvement.

Reference [26] proposed a hybrid of Tabu search and simulated annealing algorithms, and a hybrid of ant colony optimization and simulated annealing algorithms, to minimize the total cost for allocation of multi-skilled workers and outsource service usage in dynamic cellular manufacturing systems.

The study described in [27] attempted to investigate the effects of personal competency on job commitment and satisfaction through talent donation in the field of cosmetology. Results revealed a highly significant correlation among personal competency and talent donation, job commitment, and job satisfaction. Furthermore, there was a highly significant correlation between job commitment and job satisfaction. Therefore, this study proposed that it is a necessity to seek diverse options to enhance competency.

A team building method based on competency modelling has been proposed in [28] for supporting project leaders to organise the actors into teams. The authors suggested that incorporating a clustering algorithm as a step of the method results in preserving expertise and thus helps project managers to find better trade-offs between project cost (short term goal) and competency dynamics (long term goal).

The study described in [29] evaluated the impact of individual and social harmful factors on creativity inaction period in supply chains. Results showed that the harmful individual and social factors impose adverse effects on individual employees that cause different inaction periods named short-term, long-term, and organizational death of individual creativity inertia.

Finally, in [9] a mathematical framework has been presented to calculate the soft and hard skills of employees based on time and achievements as skill increases or decreases over time.

B. TOOLS AND SYSTEMS

Many commercial services and systems offers visual interfaces to identify employees with a heightened risk of a burnout, by highlighting the employees assigned to many multiple activities and evaluating them on various criteria, such as location, availability, and skills. Microsoft Project,¹ Silverbucket,² Zoho People,³ and Clarizen One⁴ are few examples of such services. They are quite similar and provide a very basic level of decision support for the allocation decision.

¹<https://www.microsoft.com/en-us/microsoft-365/project/project-management-software>

²<https://www.silverbucket.com/>

³<https://www.zoho.com/people/>

⁴<https://www.clarizen.com/product/clarizen-one/>

RésuméMatcher [30] is a personalized job-résumé matching system for ranking relevance between candidate curricula and a database of available jobs.

CASPER is case-based profiling for electronic recruitment system designed to improve the usability of the JobFinder web site search engine [31]. CASPER tracks user behavior within the JobFinder site, and constructs a user profile with which to generate personalized recommendations based on preferences of users with a similar profile. [32] presented a job recommender systems integrating content-based filtering and collaborative filtering in order to overcome limitations resulting from the problem of rating data sparsity by leveraging synergies between the two approaches in a combined model.

In [11] a decision support system is proposed for identifying the key components required for effective human resource allocation, which makes it easier for organisations to implement similar systems.

Some attempts were made in evaluating a matching degree between workers and jobs. For example, Skill Matcher⁵ allows people searching for a job by filling professional skills levels, and gives as response a list of the best matching types of career. Instead, Skills Match⁶ allows to insert previous professional experiences, and shows the types of job that use the same skills.

III. THE PROPOSED DECISION MODEL

The proposed decision model, schematized in Fig. 1 is composed of two main elements specially devised to support HR management in finding the best job-employee assignments able to maximize the global mutual satisfaction.

Firstly, a data model has been devised to formally describe available jobs and assignable employees, as well as preferences of HR managers and employees on potential assignments. Jobs are mainly described in terms of general area of activity and professional prospects which may be generated in performing the jobs. Employees are mainly described in terms of their hard and soft skills. A peculiarity of this data model is the self-evaluation of employees' soft skills on the basis of the frequency with which they occurred in job behaviors. But, to prevent employees to state to have done all the socio-relational experiences at the maximum frequency, a budget of points is assigned to each employee and is consumed on the basis of the peculiar frequency chosen for a soft skill.

Moreover, the description of available jobs and assignable employees is enriched with the preferences of individuals on potential assignments, taking into account both the preferences of HR managers on hard and soft skills they would like to find in the employee assigned to a job, and the preference of employees on the characteristics of the job they would like to be assigned. As another characteristic element of this

data model, there is the self-evaluation of the importance employees and HR managers want to place on each expressed preference by weighting it through some tokens taken from an available budget. The number of tokens bet for each preference will enable the computation of the importance given by employees and managers to their preferences, as described in detail later.

Secondly, the proposed decision model provides an efficient AI-based optimization algorithm to select the optimal allocation, where the cost of potential assignments is computed as opposite to the degree of satisfaction of the preferences of employees and HR managers. In this way, the optimal allocation is achieved by maximizing the global mutual satisfaction of employees and managers. To this aim, a fuzzy cost model has been defined to measure and evaluate the degree of satisfaction of HR managers and employees in potential employee-job assignments. The degree of mutual satisfaction of employees and HR managers depends on how and how well their expectations were met, so a metric for each particular type of preference is required.

In the following, the elements composing the proposed decision model are diffusely explained.

A. DATA MODEL

Figure 2 reports the data model specially designed to formally describe assignable employees and available jobs, and the preferences of HR managers and employees on assignments.

It is important to note that, while the proposed decision model has general applicability, the kind of information considered and selected for describing jobs and employees has been impacted by the real case study analyzed and used for validating the model itself. Moreover, some taxonomies resulted very wide (e.g., all possible academic training and competencies, all possible languages, or all possible areas of activity) and are referred to Italy (e.g., possible Master Degree titles according to Italian legislation), and should be replaced in case of applications in other countries or in an international environment.

As a consequence, in order to simplify the fulfillment of jobs, employees, and the preferences of HR managers and employees on assignments, while the proposed decision model theoretically includes the whole taxonomies, some subsets were chosen, which are reported in the following. Domain experts individuated them by evaluating the requirements of the public sector related to the application, thus they should be replaced for different applications.

Furthermore, note that classes modelling a taxonomy of admitted values have not been represented in the class diagrams, but, for brevity, they have been just reported in bold as allowed instances of some attributes. However, they are described and discussed in the following sections.

1) JOBS AND EMPLOYEES

According to domain experts, a complete description of peculiar aspects characterizing each job is not a simple task in

⁵<https://www.careeronestop.org/Toolkit/Skills/>

⁶<https://joboutlook.gov.au/career-tools/skills-match/>

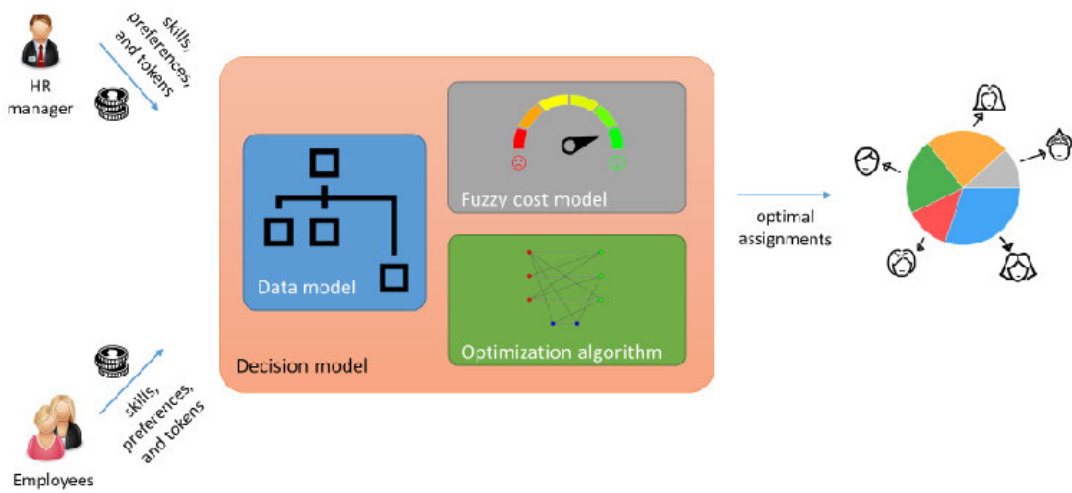


FIGURE 1. The proposed decision model to support HR allocation.

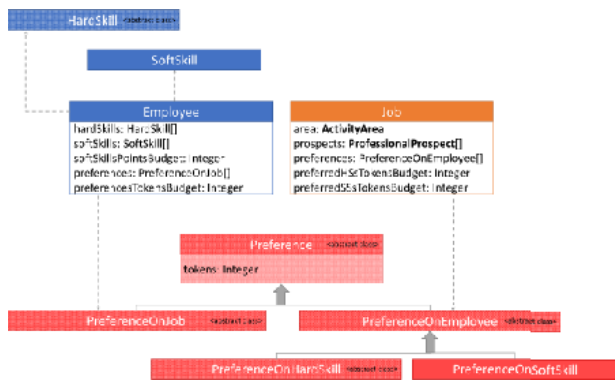


FIGURE 2. The data model underlying the proposed decision model.

public organizations, where the type of required working activity can be very heterogeneous. An employee is often asked to perform different tasks that fall into a general activity area, characterizing the office to which they are assigned.

As a consequence, to keep the proposed decision model generic and applicable in different public organizations, available jobs have been modeled through the class **Job** which is mainly characterized by two mandatory attributes:

- $j.area$ is used to link a job $j \in \mathbf{Job}$ to one instance belonging to the class **ActivityArea** representing the main area of activity the job;
- $j.prospects$ is used to link a job $j \in \mathbf{Job}$ to a list of instances belonging to the class **ProfessionalProspects** representing the professional prospects the job could allow to generate.

Each employee has been modeled through the class **Employee** which is mainly characterized by two attributes:

- $e.softSkills$ can be used to link an employee $e \in \mathbf{Employee}$ to a list of instances belonging to the

class **SoftsSkill** representing the socio-relational experiences the employee have manifested more in the past;

- $e.hardSkills$ can be used to link an employee $e \in \mathbf{Employee}$ to a list of instances belonging to the abstract class **HardSkill** representing easily assessable skills owned by the employee (e.g.: academic training, technical competencies, work experiences, and so on).

Moreover, both jobs and employees are characterized by an attribute *preferences* which can be used to link them to a list of instances belonging to the classes **PreferenceOnEmployee** and **PreferenceOnJob**, respectively. These abstract classes are specializations of the the abstract class **Preference**, which is the upper class of a class hierarchy specially defined to model the different types of preferences of HR managers and employees on assignments. Note that, each element $p \in \mathbf{Preference}$ is characterized by a an attribute $p.tokens$ representing the number of tokens an individual want to bet on that preference, whose use will be described later in the definition of the optimal assignment search algorithm.

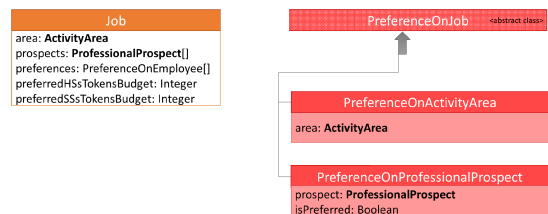


FIGURE 3. The classes defined for modelling jobs and employees preferences on them.

In the following, more details are given about the classes defined for modelling the different types of characteristics of jobs and employees, and preferences of employees and HR managers.

2) JOBS AND EMPLOYEES' PREFERENCES ON JOBS

Figure 3 reports the classes defined for modelling employees preferences on the characteristics of the job they would like to be assigned.

The class **ActivityArea** has been defined as an enumeration of labels, based on the taxonomy of all the area of activities characterizing the available jobs. Some example of areas of activity can be *purchases, contracts, legal*, and so on.

The class **PreferenceOnActivityArea** can be used to model an employee's preference on one or more areas of activity in which they would like their assigned job to fall. Any preference $p \in \mathbf{PreferenceOnActivityArea}$ is characterized by an attribute $p.area$, indicating the area preferred by the employee, whose allowed value is one of the instances defined for the class **ActivityArea**.

The class **ProfessionalProspects** has been defined as an enumeration of labels, based on the taxonomy of all professional prospects which may be generated in performing the jobs. For example, possible professional prospects can be the chance to make business trips during the job, or to work remotely, or to access to roles of responsibility, and so on.

The class **PreferenceOnProfessionalProspect** can be used to model an employee's preference on the professional prospects they would like to find in their assigned job. Any preference $p \in \mathbf{PreferenceOnProfessionalProspect}$ is characterized by two attributes $p.prospect$ and $p.isPreferred$, indicating the professional prospect of interest and if that prospect is desired or not. The admitted values for the attribute $p.prospect$ is one of the instances defined for the class **ProfessionalProspects**. The attribute $p.isPreferred$ admits also a NULL value to indicate that the chance to find or not the prospect of interest is indifferent for the employee.

Employees can specify their preferences on available jobs betting a proper number of tokens such that

$$\forall e \in \mathbf{Employee}, \sum_{p \in \{P_e^A \cup P_e^P\}} p.tokens \leq e.preferencesTokensBudget \quad (1)$$

where $P_e^A = \{e.preferences \cap \mathbf{PreferenceOnActivityArea}\}$ and $P_e^P = \{e.preferences \cap \mathbf{PreferenceOnProfessionalProspects}\}$ are the sets of preferences about the activity area and professional prospects an employee $e \in \mathbf{Employee}$ would like to find in their assigned job.

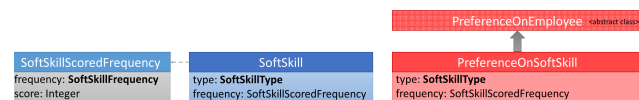


FIGURE 4. The classes defined for modelling employees' soft skills and the preferences of HR managers focused on them.

3) SOFT SKILLS AND HR MANAGERS' PREFERENCES ON THEM

Figure 4 reports the classes defined for modelling employees' soft skills, and for representing the preferences of HR

managers on the types of soft skills they would like to find in employees assigned to the available jobs.

The class **SoftSkill** models a socio-relational experience occurred in an employee experience, and it is characterized by the attribute *type* indicating the instance belonging to the class **SoftSkillType** representing the peculiar skill of interest, and by the attribute *frequency* specifying the instance belonging to the class **SoftSkillScoredFrequency** representing the frequency with which the type of soft skill have occurred in the employee's experience and the score associated to that frequency value.

In detail, the **SoftSkillScoredFrequency** class associates to each instance of **SoftSkillFrequency** a peculiar score, and employees' soft skills can be specified such that the sum of points corresponding to all frequencies inserted is constrained to not exceed the total budget assigned to the employees, in accordance with the Equation 2.

$$\forall e \in \mathbf{Employee}, \sum_{s \in e.softSkills} s.frequency.score \leq e.softSkillsPointsBudget \quad (2)$$

The class **SoftSkillType** has been defined as an enumeration of labels, based on the taxonomy of the socio-relational experiences employees could have manifested more during their job experience. For example, possible socio-relational experiences can be adaptability, emotional self-control, accurate self-assessment, and so on.

The class **SoftSkillFrequency** has been defined to represent the allowed values for the frequency with which a soft skill can be owned or requested. The following fixed values have been defined: "it didn't happen", "rarely", "often", "systematically".

The class **SoftSkillScoredFrequency** has been defined to associate the following fixed scores to the instances defined for the class **SoftSkillFrequency**: 0 points for "it didn't happen", 1 point for "rarely", 2 points for "often", and 3 points for "systematically".

The class **PreferenceOnSoftSkill** models a preference of HR managers on the types of soft skill they would like to find in an employee assigned to a job. Any preference $p \in \mathbf{PreferenceOnSoftSkill}$ is characterized by the attribute $p.type$ indicating the instance belonging to the class **SoftSkillType** representing the peculiar skill of interest, and by the attribute $p.frequency$ specifying the instance belonging to the class **SoftSkillScoredFrequency** representing the ideal minimum frequency with which the preferred soft skill should have occurred in the employees' experience.

HR managers can specify their preferences on employees' soft skills betting a proper number of tokens such that

$$\forall j \in \mathbf{Job}, \sum_{p \in P_j^S} p.tokens \leq j.preferredSSsTokensBudget \quad (3)$$

where $\mathbf{P}_j^S = \{j.preferences \cap \mathbf{PreferenceOnSoftSkill}\}$ is the set of HR managers' preferences on soft skills they would like to find in an employee assigned to a job $j \in \mathbf{Job}$.



FIGURE 5. The classes defined for modelling employees' hard skills and the preferences of managers on that type of skill.

4) HARD SKILLS AND HR MANAGERS' PREFERENCES ON THEM

Figure 5 reports the classes defined for modelling employees' hard skills, and for representing the preferences of HR managers on the types of hard skills they would like to find in employees assigned to the available jobs.

Inspired by how information about academic training, technical competencies and job experiences are typically described within a Europass⁷ Curriculum Vitae (CV), to model the hard skills owned by employees, the class **HardSkill** has been specialized by eight concrete classes. Each type of hard skill has been modelled through a various set of attributes, whose admitted values can be freely inserted or bound to a given taxonomy specifically selected in accordance with domain experts. According to the Italian legislative system, for example, to represent a university-level degree owned by an employee, the type of that degree is required to be specified since different types existed during the last decades. To this aim, the admitted values for the type of a degree have been bound to those in the government lists.

Moreover, other constraints on the values allowed for some attributes have been introduced to avoid representing irrelevant information or to enable the evaluation, at a later stage,

of HR managers' satisfaction with the particular skill under consideration. Indeed, the proposed decision model does not aim to provide complete modelling and evaluation of an individual's CV, but only to bring out and consider helpful information for the job assignment process according to the indications of HR management. As an example, to represent an employee's professional experience, the main area of activity characterizing that experience is required to avoid representing experiences not related to the areas of interest for HR managers. To this aim, the admitted values for the area of activity of a professional experience have been bound to those characterizing the available jobs, i.e the instances of the class **ActivityArea**.

The abstract class **PreferenceOnHardSkill** models a preference of HR managers on the types of hard skills they would like to find in employees assigned to an available job. HR managers can specify these preferences betting a proper number of tokens such that

$$\forall j \in \mathbf{Job},$$

$$\sum_{p \in \mathbf{P}_j^H} p.tokens \leq j.preferredHSsTokensBudget \quad (4)$$

where $\mathbf{P}_j^H = \{j.preferences \cap \mathbf{PreferenceOnHardSkill}\}$ is the set of preferences of HR managers on the types of hard skills they would like to find in an employee assigned to a job $j \in \mathbf{Job}$.

For each concrete subclass $\mathbf{H} \subseteq \mathbf{HardSkill}$ an associated concrete class $\mathbf{P}^H \subseteq \mathbf{PreferenceOnHardSkill}$ has been defined, whose attributes, indicating the values and/or the levels HR managers prefer for a skill belonging to the class \mathbf{H} , are closely related to the attributes of the class \mathbf{H} .

In the following, the concrete classes defined for modelling employees hard skills and the preferences focused on them are presented, and the constraints introduced on their admitted values are discussed.

The class **UniversityFormation** can be used to represent university-level degrees owned by an employee, and it is mainly characterized by the attributes *grade* reporting the degree's vote obtained, *start* and *end* representing the start and end date of the degree program, and *degree* linking the instance belonging to the class **UniversityLevelDegree** describing the *type*, the *title*, and the *university* where a degree has been obtained.

The class **DegreeType** models the allowed values for the type of an university-level degree. In accordance with domain experts and the legislative system,⁸ the following values have been modeled: triennial degree (DM 509/99), specialistic degree (DM 209/99), triennial degree (DM 270/04), master degree (DM 270/04), university diploma or diploma (DPR 162/82), or bachelor's degree. The class **DegreeTitle** models the allowed values for the title of an university-level degree, coherently with official equipollence table.⁹ The class

⁸<https://www.miur.gov.it/lauree-e-lauree-magistrali>

⁹<https://www.miur.gov.it/web/guest/equipollenze-ed-equiparazioni-trattiti-accademici-italiani>

⁷<https://europass.cedefop.europa.eu/>

University models the allowed values for the university where a degree has been obtained, coherently with existing physical or telematic (modeled via the class **TelematicUniversity**) Italian universities. In accordance with domain experts, also foreign universities have been modeled via the class **ForeignUniversity**.

The class **PreferenceOnUniversityFormation** can be used to model a preference of HR managers on the employees' university formation. Any preference $p \in \text{PreferenceOnUniversityFormation}$ is characterized by the attributes $p.type$ and $p.title$ indicating, respectively, the type and title of the degree preferred by the managers. Note that, the admitted values for these attributes are, respectively, the instances defined for the classes **DegreeType** and **DegreeTitle**.

The class **PostUniversityFormation** can be used to represent post-graduate training courses attended by an employee, and it is mainly characterized by the attributes $start$ and end representing the start and end date of the attended course, and $course$ linking the instance belonging to the class **PostUniversityCourse** describing both the $type$, the $title$, the $area$ and the $sector$ of the course, and the $university$ where it has been attended.

The class **PostUniCourseType** models the allowed values for the type of a post-graduate training course. In accordance with domain experts, the following values have been modeled: doctorate, first-level master, second-level master, and course of specialization.

The classes **DisciplinaryArea** and **DisciplinarySector** model the allowed values for the disciplinary area and sector of a post-graduate training course, coherently with the official legislative list.¹⁰

The class **PreferenceOnPostUniversityFormation** can be used to model a preference of HR managers on post-graduate training courses eventually attended by employees. Any preference $p \in \text{PreferenceOnPostUniversityFormation}$ is characterized by the attributes $p.type$, $p.area$ and $p.sector$ indicating, respectively, the type, the disciplinary area and the disciplinary sector of the post-graduate training course preferred by the managers. The admitted values for these attributes are, respectively, the instances defined for the classes **PostUniCourseType**, **DisciplinaryArea** and **DisciplinarySector**. Moreover, a NULL instance is also admitted for $p.sector$, indicating that any sector within the associated disciplinary area is satisfactory.

The class **ProfessionalQualification** has been defined to model professional qualifications eventually achieved by an employee, and it is characterized by the attributes $type$ and $year$ indicating, respectively, the type of the professional qualification and the year of achievement. The allowed values for the type of professional qualifications have been modeled through the class **ProfessionalQualificationType**, coherently with the official list.¹¹

The class **PreferenceOnProfessionalQualification** can be used to model a preference of HR managers on professional titles eventually owned by employees. Any preference $p \in \text{PreferenceOnProfessionalQualification}$ is characterized by the attribute $p.type$, indicating the type of professional qualification preferred by the managers, whose admitted values are the instances defined for the class **ProfessionalQualificationType**.

IT certifications eventually owned by an employee can be represented through the class **ITCertification** which is characterized by the attributes $type$, $institution$, and $year$ representing, respectively, the type of certification, the institution that provided it, and the year of achievement. The allowed values for the type of IT certifications have been modeled through the class **ITCertificationType**, coherently with the those accepted for some public competitions.¹²

The class **PreferenceOnITCertification** models the preferences of HR managers on IT certifications eventually owned by employees. Any preference $p \in \text{PreferenceOnITCertification}$ is characterized by the attribute $p.type$, representing the type of IT certification preferred by the managers, whose admitted values are the instances defined for the class **ITCertificationType**.

The class **LinguisticCertification** models linguistic certifications eventually owned by an employee, and it is characterized by the attributes $name$, $institution$, $language$, $level$, and $year$ representing, respectively, the name of the certification, the institution that provided it, the language and the level being certified, and the year of achievement. The allowed values for the language being certified have been modeled through the class **Language**, by defining, in accordance with domain experts, the following instances: *English*, *French*, *Spanish*, *German*, *Russian*, *Chinese* and *Japanese*. The allowed values for the level being certified have been modeled through the class **LinguisticCertificationLevel**, coherently with the common European framework of reference for the knowledge of languages,¹³ i.e. the levels from *A1* to *C2*.

The class **PreferenceOnLinguisticCertification** can be used to model a preference of HR managers on linguistic certifications eventually owned by employees. Any preference $p \in \text{PreferenceOnLinguisticCertification}$ is characterized by the attributes $p.language$ and $p.level$, representing the certified language and level preferred by the managers. The admitted values for these attributes are, respectively, the instances defined for the classes **Language** and **LinguisticCertificationLevel**.

The class **ITSkill** has been defined to model a IT skill owned by an employee when it is not certified but self-assessed. This class is characterized by the attributes $type$ and $level$ describing, respectively, the type of certification and the level achieved. The allowed values for the type and the

¹⁰<http://www.miur.it/UserFiles/115.htm>

¹¹<http://www.quadroititoli.it/quadroitoliprofessionali.aspx?IDL=1&qtp=182>

¹²<https://graduatorie.static.istruzione.it/informazioni-utili.html>

¹³<https://www.coe.int/en/web/common-european-framework-reference-languages>

level of a self-assessed IT skill have been modeled through the classes **ITSkillType** and **ITSkillLevel**, whose instances have been defined coherently with types (i.e. *communication, content creation, information processing, troubleshooting, and security*) and the levels (i.e. *basic user, autonomous user, advanced user*) foreseen for IT skills within the Europass CV.

The class **PreferenceOnITSkill** can be used to model a preference of HR managers on IT skills eventually owned by employees. Any preference $p \in \mathbf{PreferenceOnITSkill}$ is characterized by the attributes $p.type$ and $p.level$, representing the preferred type and level by the managers. The admitted values for these attributes are, respectively, the instances defined for the classes **ITSkillType** and **ITSkillLevel**.

The class **LinguisticSkill** has been defined to model a linguistic skill owned by an employee when it is not certified but self-assessed. This class is characterized by the attributes *language* and *level* representing, respectively, the language and the level being self-assessed. The allowed values for these attribute are the instances defined, respectively, for the classes **Language** and **LinguisticSkillLevel**. This last class has been created as a specialization of the class **Linguistic-CertificationLevel**, by defining a further instance to model a native level language skill (i.e. the instances of **Linguistic-SkillLevel** from $A1$ to $C2$, plus the level *mother-tongue*).

The class **PreferenceOnLinguisticSkill** can be used to model a preference of HR managers on linguistic skills eventually owned by employees. Any preference $p \in \mathbf{PreferenceOnLinguisticSkill}$ is characterized by the attributes $p.language$ and $p.level$, representing the language and level preferred by the managers. The admitted values for these attributes are, respectively, the instances defined for the classes **Language** and **LinguisticSkillLevel**.

The class **ProfessionalExperience** can be used to represent previous professional experiences of employees, and it is described by the attributes *type* reporting the type of the experience, *area* indicating the main area of activity characterizing the experience, *durationInYears* representing the duration in years of the experience, and *employer* linking the instance of the class **Employer** describing the *name*, the *dimension*, the *sector*, and the territorial *level* of the employer (i.e. the institute, organization or company where the experience was gained).

The allowed values for the attribute *type* are the instances defined, in accordance with domain experts, for the class **ProfessionalExperienceType**. The following values have been considered: *stage* and *job*.

To avoid representing experiences not related to the areas of interest for HR managers, the allowed values for the attribute *area* are the instances defined for the class **ActivityArea**.

The classes **EmployerDimension**, **EmployerSector**, and **EmployerLevel**, model the allowed values that have been considered, in accordance with domain experts, for the dimension of the employer depending on its number of employees (*micro-enterprise, little enterprise, medium*

enterprise or big enterprise), for the employer's sector (*public or private*), and for its territorial level (*national or foreign*).

The class **PreferenceOnProfessionalExperience** can be used to model a preference of HR managers on previous professional experiences gained by employees. Any preference $p \in \mathbf{PreferenceOnProfessionalExperience}$ is characterized by the attributes $p.type$, $p.area$, $p.durationInYears$, $p.dimension$, $p.sector$, and $p.level$, describing the preferred type and duration by the managers for the professional experiences gained by employees. The admitted values for the attributes $p.type$, $p.area$, $p.dimension$, $p.sector$, and $p.level$, are, respectively, the instances defined for the classes **ProfessionalExperienceType**, **ActivityArea**, **EmployerDimension**, **EmployerSector** and **EmployerLevel**. Moreover, a NULL instance is also admitted for $p.type$, $p.dimension$, $p.sector$, and $p.level$, indicating that any value owned by the employee is satisfactory.

B. OPTIMIZATION ALGORITHM AND FUZZY METRICS

1) PROBLEM FORMULATION AND SOLUTION

Suppose a public organization's HR management having identified a set \mathbf{J} of available jobs in accordance with the needs of their offices. Then, suppose the existence of a set \mathbf{E} of employees assignable to the available jobs such that the number of employees is equal to the number of open job positions, i.e. $card(\mathbf{E}) = card(\mathbf{J})$.

The whole decision process has been formulated as an assignment problem, where employees and jobs are modelled through a bipartite graph $\mathbf{G} = (\mathbf{J} \cup \mathbf{E}, \mathbf{A})$:

- half of the nodes of \mathbf{G} represents single available job positions $j \in \mathbf{J}$ and the other half of nodes represents distinct employees $e \in \mathbf{E}$ to be allocated;
- $\mathbf{A} = \{(j, e, C_{j,e})\}$ is the set of edges of \mathbf{G} representing all possible job-employee assignments bridging the nodes $j \in \mathbf{J}$ with the nodes $e \in \mathbf{E}$, and the cost $C_{j,e}$ associated to the considered assignment.

Note that, a possible solution of the assignment problem is any set $\mathbf{A}' \subset \mathbf{A}$ composed such that every node in the graph is touched by one and only one edge. On the contrary, the optimal solution corresponds to the minimum of the sum of costs of the chosen job-employee pairs. Therefore, it consists in finding the set $\mathbf{A}'_{min} \subset \mathbf{A}$ associated with the minimum cost:

$$C_{\mathbf{A}'_{min}} = \min_{\mathbf{A}' \subset \mathbf{A}} C_{\mathbf{A}'} = \min_{\mathbf{A}' \subset \mathbf{A}} \left[\sum_{(j,e,C_{j,e}) \in \mathbf{A}'} C_{j,e} \right] \quad (5)$$

To solve the optimal assignment problem formulated in Eq. 5, the proposed decision model applies a cost-scaling push-relabel algorithm for minimum-cost perfect assignment [6] which requires bounded integer costs to be minimized. But, how to evaluate the cost associated to a potential job-employee assignment?

The idea here proposed is to evaluate the cost of potential assignments as opposite to the degree of satisfaction of the

preferences of employees and HR managers. In this way, the optimal allocation is achieved by maximizing the global mutual satisfaction of employees and managers. More formally, given a job $j \in \mathbf{J}$ and an employee $e \in \mathbf{E}$, the cost $C_{j,e}$ associated to their assignment has been defined as:

$$C_{j,e} = \text{int} (C_{max} \cdot (1 - M_{j,e})) \in \{0, 1, \dots, C_{max}\} \quad (6)$$

where $\text{int}()$ is a function converting the argument value into an integer number, C_{max} is an integer constant chosen as maximum cost, and $M_{j,e} \in [0, 1]$ is a fuzzy metric computing the degree of mutual satisfaction between the employee e and the HR managers as a consequence of the assignment of e to the job j .

Note that, the peculiar value of C_{max} must be chosen according to the particular application case taking into account the number N of nodes of the graph \mathbf{G} . On the one hand, C_{max} has to be big enough to enable sufficient granularity for distinguishing costs of job-employee pairs, with respect to N ; on the other hand, C_{max} has to be small enough to have a low bound of the algorithm complexity, since it depends on C_{max} according to $O(N^3 \log(NC_{max}))$.

Moreover, the presented decision model proposes to evaluate the degree of mutual satisfaction, resulting from a job-employee assignment, by computing the different types of preferences expressed by the involved employee and the HR managers, as follows:

$$M_{j,e} = w^H M_{j,e}^H + w^S M_{j,e}^S + w^C M_{j,e}^C \text{ with } w^H + w^S + w^C = 1 \quad (7)$$

where $M_{j,e}^H \in [0, 1]$, $M_{j,e}^S \in [0, 1]$, and $M_{j,e}^C \in [0, 1]$, are fuzzy metric computing, respectively, the degree of satisfaction of the preferences expressed by: i) the HR managers on hard skills they would like to find in the employee assigned to the job; ii) the HR managers on soft skills they would like to find in the employee assigned to the job; iii) the employee on the characteristics of the job they would like to be assigned. The weights $w^H \in [0, 1]$, $w^S \in [0, 1]$, and $w^C \in [0, 1]$, are configuration parameters of the proposed decision model able to determine how much each type of preference contributes in the proposed decision model. The choice of the actual parameters to be used is offered to the HR managers, who can choose the most appropriate configuration for their needs.

In the following, more details are given about the fuzzy metrics, defined to compute the degree of satisfaction of the different types of preferences of employees and managers, and presented on the basis of the defined data model.

2) HR MANAGERS SATISFACTION ABOUT EMPLOYEES' HARD SKILLS

Given a potential assignment to the job $j \in \mathbf{J}$ of an employee $e \in \mathbf{E}$, the fuzzy metric $M_{j,e}^H \in [0, 1]$ computing the degree of satisfaction of the preferences expressed by the HR managers

on employees' hard skills has been defined as follows:

$$M_{j,e}^H = \begin{cases} \frac{\sum_{p \in \mathbf{P}_j^H} (m_{p,e}^H \cdot p.tokens)}{\sum_{p \in \mathbf{P}_j^H} p.tokens} & \text{if } \text{card}(\mathbf{P}_j^H) > 0 \\ 1 & \text{otherwise} \end{cases} \quad (8)$$

where $m_{p,e}^H \in [0, 1]$ is a fuzzy metric computing the degree of satisfaction of the preference $p \in \mathbf{P}_j^H$ on the hard skills owned by the employee e . For each concrete class of **PreferenceOnHardSkill**, a different kind of fuzzy metric has been defined. In the following, these fuzzy metrics are briefly outlined.

In case $p \in \mathbf{PreferenceOnUniversityFormation}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the preferred degree's type and title with the ones held by the employee. The degree of satisfaction is 1 if the employee owns a degree equal or equivalent to the preferred one, otherwise is 0, as follows:

$$m_{p,e}^H = \max_{s \in \mathbf{S}_e^{UF}} \begin{cases} 1 & \text{if } (p.type = s.degree.type) \wedge \\ & (p.title = s.degree.title) \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where $\mathbf{S}_{e \in \mathbf{E}}^{UF} = \{e.hardSkills \cap \mathbf{UniversityFormation}\}$.

In case $p \in \mathbf{PreferenceOnPostUniversityFormation}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the preferred type of course (e.g., doctorate) and the disciplinary area and sector with those held by the employee. The degree of satisfaction is 1 if all the preferred characteristics are held by the employee, 0.5 if the employee holds them except the disciplinary sector, 0 otherwise, as follows:

$$m_{p,e}^H = \max_{s \in \mathbf{S}_e^{PUF}} \begin{cases} 1 & \text{if } (p.type = s.course.type) \wedge \\ & (p.area = s.course.area) \wedge \\ & [(p.sector = s.course.sector) \vee \\ & (p.sector = NULL)] \\ 0.5 & \text{if } (p.type = s.course.type) \wedge \\ & (p.area = s.course.area) \wedge \\ & (p.sector \neq s.course.sector) \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where $\mathbf{S}_{e \in \mathbf{E}}^{PUF} = \{e.hardSkills \cap \mathbf{PostUniversityFormation}\}$.

In case $p \in \mathbf{PreferenceOnProfessionalQualification}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the preferred qualification with the ones possessed by the employee. The degree of satisfaction is 1 if the employee owns that qualification, otherwise is 0, as follows:

$$m_{p,e}^H = \max_{s \in \mathbf{S}_e^{PQ}} \begin{cases} 1 & \text{if } p.type = s.type \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

where $\mathbf{S}_{e \in \mathbf{E}}^{PQ} = \{e.hardSkills \cap \mathbf{ProfessionalQualification}\}$.

In case $p \in \text{PreferenceOnITCertification}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the type of the preferred certification with the ones possessed by the employee. The degree of satisfaction is 1 if the employee owns that certification, otherwise is 0, as follows:

$$m_{p,e}^H = \max_{s \in S_e^{ITC}} \begin{cases} 1 & \text{if } p.type = s.type \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

where $S_{e \in E}^{ITC} = \{e.hardSkills \cap \text{ITCertification}\}$.

In case $p \in \text{PreferenceOnLinguisticCertification}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the desired language certification and its minimum level with the ones owned by the employee. The degree of satisfaction is 1 if the employee owns a certification on that language with a level equal to or greater than the preferred one, is between 0 and 1 when the level held by the employee is less than the minimum preferential one (in proportion to the ratio between the two levels, where level $A1$ corresponds to 1 and $C2$ to 6), is 0 otherwise, as follows:

$$m_{p,e}^H = \max_{s \in S_e^{LC}} \begin{cases} \min \left[1, \frac{s.level}{p.level} \right] & \text{if } p.language \\ & = s.language \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

where $S_{e \in E}^{LC} = \{e.hardSkills \cap \text{LinguisticCertification}\}$.

In case $p \in \text{PreferenceOnITSkill}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the type of the desired IT skill and its minimum level with the ones owned by the employee. The degree of satisfaction is 1 if the employee owns that IT skill with a level equal to or greater than the preferred one, is between 0 and 1 when the level held by the employee is less than the requested one (in proportion to the ratio between the two levels, where level *base user* corresponds to 1 and *advanced user* to 3), is 0 otherwise, as follows:

$$m_{p,e}^H = \max_{s \in S_e^{ITS}} \begin{cases} \min \left[1, \frac{s.level}{p.level} \right] & \text{if } p.type \\ & = s.type \\ 0 & \text{otherwise} \end{cases} \quad (14)$$

where $S_{e \in E}^{ITS} = \{e.hardSkills \cap \text{ITSkill}\}$.

In case $p \in \text{PreferenceOnLinguisticSkill}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the desired language skill and its minimum level with the ones owned by the employee. The degree of satisfaction is 1 if the employee owns the requested linguistic skill with a level equal to or greater than the preferred one, is between 0 and 1 when the level held by the employee is less than the preferred one (in proportion to the ratio between the two levels, where language level $A1$ corresponds to 1 and *mother-tongue* to 7), is 0 otherwise, as follows:

$$m_{p,e}^H = \max_{s \in S_e^{LS}} \begin{cases} \min \left[1, \frac{s.level}{p.level} \right] & \text{if } p.language \\ & = s.language \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

where $S_{e \in E}^{LS} = \{e.hardSkills \cap \text{LinguisticSkill}\}$.

In the case when $p \in \text{PreferenceOnProfessionalExperience}$, the degree of satisfaction $m_{p,e}^H$ of the preference p is evaluated by comparing the desired area of activity and its minimum duration with the one experienced by the employee. The degree of satisfaction is 1 if the employee had experiences in the desired area of activity with a total duration equal to or greater than the preferred one, is between 0 and 1 if the employee had experiences with a total duration less than the preferred one, 0 if the employee has no experience in the preferred area of activity. Moreover, each experience is divided by 2 if the type of experience is different from the preferred one, and if the employer where the experience was gained does not satisfy the desired dimension, sector, or territorial level, as follows:

$$m_{p,e}^H = \min \left[1, \sum_{s \in S_e^{PE}} \left[\phi(p, s) \cdot \left(\frac{1}{2} \right)^{\delta_{p,s}} \right] \right] \quad (16)$$

where

$$\begin{aligned} \phi(p, s) &= \begin{cases} \frac{s.durationInYears}{p.durationInYears} & \text{if } p.area = s.area \\ 0 & \text{otherwise} \end{cases} \\ \delta_{p,s} &= \delta_{p,s}^{type} + \delta_{p,s}^{dimension} + \delta_{p,s}^{sector} + \delta_{p,s}^{level} \\ \delta_{p,s}^{type} &= \begin{cases} 1 & \text{if } (p.type \neq NULL) \wedge (p.type \neq s.type) \\ 0 & \text{otherwise} \end{cases} \\ \delta_{p,s}^{dimension} &= \begin{cases} 1 & \text{if } (p.dimension \neq NULL) \wedge \\ & (p.dimension \neq s.employer.dimension) \\ 0 & \text{otherwise} \end{cases} \\ \delta_{p,s}^{sector} &= \begin{cases} 1 & \text{if } (p.sector \neq NULL) \wedge \\ & (p.sector \neq s.employer.sector) \\ 0 & \text{otherwise} \end{cases} \\ \delta_{p,s}^{level} &= \begin{cases} 1 & \text{if } (p.level \neq NULL) \wedge \\ & (p.level \neq s.employer.level) \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

and $S_{e \in E}^{PE} = \{e.hardSkills \cap \text{ProfessionalExperience}\}$.

3) HR MANAGERS SATISFACTION ABOUT EMPLOYEES' SOFT SKILLS

Given a potential assignment to the job $j \in \mathbf{J}$ of an employee $e \in \mathbf{E}$, the fuzzy metric $M_{j,e}^S \in [0, 1]$ computing the degree of satisfaction of the preferences expressed by the HR managers on employees' soft skills has been defined as follows:

$$M_{j,e}^S = \begin{cases} \frac{\sum_{p \in \mathbf{P}_j^S} (m_{p,e}^S \cdot p.tokens)}{\sum_{p \in \mathbf{P}_j^S} p.tokens} & \text{if } card(\mathbf{P}_j^S) > 0 \\ 1 & \text{otherwise} \end{cases} \quad (17)$$

where $m_{p,e}^S \in [0, 1]$ is a fuzzy metric computing the degree of satisfaction of the preference $p \in \mathbf{P}_j^S$ on the soft skills

owned by the employee e . The degree of satisfaction $m_{p,e}^S$ of the preference p is evaluated by comparing the desired behaviour and its minimum preferred frequency with the ones assessed by the employee. The degree of satisfaction is 1 if the frequency indicated by the employee is higher or equal to the minimum preferential one, it is between 0 and 1 if the frequency indicated by the employee is less than the minimum preferential one (in proportion to the ratio between the two frequencies, where “rarely” corresponds to 1 and “systematically” to 3), and it is 0 if the employee has indicated “it didn’t happen” (corresponding to 0) as the frequency of that aspect, as follows:

$$m_{p,e}^S = \max_{s \in e.softSkills} \begin{cases} \phi_{min}(p, s) & \text{if } p.type = s.type \\ 0 & \text{otherwise} \end{cases} \quad (18)$$

where

$$\phi_{min}(p, s) = \min \left[1, \frac{s.frequency.score}{p.frequency.score} \right]$$

4) EMPLOYEES SATISFACTION ABOUT JOBS

Given a potential assignment to the job $j \in \mathbf{J}$ of an employee $e \in \mathbf{E}$, the fuzzy metric $M_{j,e}^C \in [0, 1]$ computing the degree of satisfaction of the preferences expressed by the employee on the characteristics of the job they would like to be assigned has been defined as follows:

$$M_{j,e}^C = \begin{cases} \frac{\sum_{p \in \mathbf{P}_e^C} (m_{p,j}^C \cdot p.tokens)}{\sum_{p \in \mathbf{P}_e^C} p.tokens} & \text{if } card(\mathbf{P}_e^C) > 0 \\ 1 & \text{otherwise} \end{cases} \quad (19)$$

where $m_{p,j}^C \in [0, 1]$ is a fuzzy metric computing the degree of satisfaction of the preference $p \in \mathbf{P}_e^C = \{\mathbf{P}_e^A \cup \mathbf{P}_e^P\}$ on the characteristics of the job j .

In case $p \in \mathbf{P}_e^A \subseteq \mathbf{PreferenceOnActivityArea}$, the degree of satisfaction $m_{p,j}^C$ of the preference p is evaluated by comparing the desired area of activity with the one characterizing the job. The degree of satisfaction is 1 if the area of activity is the same, is 0 otherwise, as follows:

$$m_{p,j}^C = \begin{cases} 1 & \text{if } p.area = j.area \\ 0 & \text{otherwise} \end{cases} \quad (20)$$

In case $p \in \mathbf{P}_e^P \subseteq \mathbf{PreferenceOnProfessionalProspect}$, the degree of satisfaction $m_{p,j}^C$ of the preference p is evaluated by comparing the desired professional prospects with the ones characterizing the job. The degree of satisfaction is 1 if the desired prospects can be realized in the job while those not desired are not realizable, is 0 otherwise, as follows:

$$m_{p,j}^C = \begin{cases} 1 & \text{if } [(p.isPreferred = TRUE) \wedge \\ & (p.prospect \in j.prospects)] \vee \\ & [(p.isPreferred = FALSE) \wedge \\ & (p.prospect \notin j.prospects)] \\ 0 & \text{otherwise} \end{cases} \quad (21)$$

IV. CASE STUDY

The proposed model has been experimented and validated in a real case study at the Italian MEF, with a number of new employees, hired through public competition, to be assigned to open job positions. In detail, in December 2019, a set of new officers were hired at MEF, and a subset of them was assigned to the Department of General Administration, Personnel and Services (DAG).

The number of newly hired officers was

$$N = 35$$

DAG decided to use the proposed decision model to support HR managers with the allocation of new officers to different positions at different Offices.

A. EXPERIMENTAL SETTINGS

Before the execution of the experiment, some degrees of freedom of the proposed decision model were set.

First, given the number of assignable employees (and jobs to which they should be assigned), the following value of C_{max} was set as the maximum cost in Eq. 6:

$$C_{max} = 100$$

It was chosen for two reasons: on the one hand, it is big enough to enable sufficient granularity for distinguishing costs of employee-job pairs, with respect to N ; on the other hand, it is small enough to have a low bound of the algorithm complexity, depending on C_{max} according to $O(N^3 \log(NC_{max}))$.

Moreover, the configuration parameters in Eq. 7, able to determine how much each type of preference contributes in the proposed decision model, have been set in agreement with MEF Directors, as follows:

$$w_H = 0.4$$

$$w_S = 0.2$$

$$w_C = 0.4$$

This means that, for this application, the satisfaction of HR managers’ preferences about employees’ hard skills and the satisfaction of employees’ preferences about jobs have been set to have the same importance, which is higher than the importance of HR managers’ preferences about employees’ soft skills.

B. EXPERIMENTATION PHASES

After the configuration of the proposed decision model, the experimentation was conducted. To this aim, a web application has been developed and provided to employees and HR managers for supporting them in the different phases of the experimentation.

In particular, the following phases were put into practice, according to MEF requirements: *i*) initial jobs description, *ii*) employees description *iii*) support statistics calculation, *iv*) HR managers preferences definition and tokens bet, *v*) algorithm execution and results inspection.

In the first step of initial jobs description **initial jobs description**, HR managers have been assisted in the definition and description of the areas of activity and the professional prospects characterizing the available jobs. In particular, 15 differ clusters of identical job positions were defined, having as area of activity either statistics, economy, law or welfare, for a total number of $N = 35$ jobs.

In the second step of employees description **employees description**, employees have been gathered and, after giving consent to the processing of personal data, each of them has been assisted to use the provided web application to insert their hard and soft skills, and preferences about jobs as well as the tokens bet on them.

In the third step of support statistics calculation **support statistics calculation**, data inserted were analyzed and simple statistics were computed. In detail, for each type and level of the hard and soft skills, the count of employees who have inserted it in their profile was computed. This information was anonymized and used as a support for HR managers during the task of preferences definition and tokens bet, so that HR managers could more easily evaluate the level of importance they want to give to a certain skill required for their job on the basis of the number of employees actually possessing that skill.

In the fourth step of HR managers preferences definition and tokens bet **HR managers preferences definition and tokens bet**, HR managers have been assisted to use the provided web application to insert their preferences on employees hard and soft skills, and to specify the amount of tokens to bet on them.

In the final step of algorithm execution **algorithm execution**, the allocation algorithm was run and results were presented to HR managers.

V. RESULTS AND DISCUSSION

In this section, the results of the experimentation, in terms of employee-job pairs suggested by the algorithm as optimal are reported and discussed, and then compared with actual HR managers choices.

A. GENERATED ASSIGNMENTS

The algorithm execution generated an allocation made of a set A'_{min} of employee-job pairs, such that each employee was assigned to a job and vice-versa, and such that the minimum total cost is individuated, corresponding to the maximum of the sum for all assignments of the global employee-job matching degree (made of contributions about HR managers' preferences about employee hard and soft skills and employee preferences about job).

The resulting assignments with respective degrees of satisfaction is reported in Table 1. Moreover, Figure 6 reports the global and partial degrees of satisfaction of assignments suggested by the proposed decision model.

This optimal allocation corresponds to a set of global degrees of satisfaction ranging from 0.372 to 0.952

(Mean ≈ 0.627 , SD ≈ 0.120). In particular, the assignment *job31-emp31* achieved the maximum global degree of satisfaction $M = 0.952$ (Eq. 7) and it completely satisfied HR managers' preferences about employees' hard skills ($M^H = 1.000$), while it almost completely satisfied HR managers' preferences about employees' soft skills ($M^S = 0.973$) and employees' preferences about the jobs ($M^C = 0.893$).

Instead, the assignment *job01-emp01* achieved the minimum global degree of satisfaction $M = 0.372$ and it did not satisfy HR managers' preferences about employees hard skills ($M^H = 0.013$), while it partially satisfied their preferences about the employee's soft skills ($M^S = 0.713$) and the employee's preferences about the jobs ($M^C = 0.560$).

Overall, 92 out of the 115 partial degrees of satisfaction of the selected assignments resulted over 0.5.

Moreover, 29 out of the 35 global degrees of satisfaction of the selected assignments resulted over 0.5.

The sum of global degree of satisfaction of all selected pairs resulted 21.942. The average global degree of satisfaction M resulted 0.627, while average partial degrees of satisfaction M^H , M^S and M^C resulted respectively 0.667, 0.772 and 0.513.

TABLE 1. The assignments suggested by the proposed decision model, the associated partial degrees of satisfaction of the preferences expressed by HR managers on employees (M^H and M^S) and by employees on jobs (M^C), and the global degree of satisfaction of such preferences (M).

Job	Employee	M^H	M^S	M^C	M
job01	emp01	0.013	0.713	0.560	0.372
job02	emp02	0.616	0.707	0.600	0.628
job03	emp03	0.622	0.713	0.547	0.610
job04	emp04	1.000	0.933	0.387	0.741
job05	emp05	0.833	0.667	0.293	0.584
job06	emp06	0.171	0.786	0.467	0.412
job07	emp07	0.667	0.857	0.600	0.678
job08	emp08	0.748	0.500	0.267	0.506
job09	emp09	0.493	0.778	0.707	0.635
job10	emp10	0.250	0.844	0.467	0.456
job11	emp11	0.833	0.618	0.667	0.724
job12	emp12	0.633	0.729	0.667	0.666
job13	emp13	1.000	0.800	0.560	0.784
job14	emp14	0.938	0.600	0.680	0.767
job15	emp15	0.771	0.933	0.453	0.676
job16	emp16	0.766	0.733	0.467	0.640
job17	emp17	0.870	0.900	0.467	0.714
job18	emp18	0.667	0.833	0.493	0.631
job19	emp19	0.667	0.922	0.360	0.595
job20	emp20	0.667	0.733	0.440	0.589
job21	emp21	0.708	0.678	0.533	0.632
job22	emp22	0.833	0.744	0.493	0.680
job23	emp23	0.708	0.733	0.413	0.595
job24	emp24	0.712	0.633	0.667	0.678
job25	emp25	0.833	0.760	0.467	0.672
job26	emp26	0.292	0.733	0.320	0.391
job27	emp27	0.708	0.867	0.113	0.510
job28	emp28	0.750	0.656	0.113	0.484
job29	emp29	0.208	0.900	0.587	0.498
job30	emp30	0.681	0.720	0.560	0.640
job31	emp31	1.000	0.973	0.893	0.952
job32	emp32	0.808	0.920	0.533	0.721
job33	emp33	0.413	0.820	0.747	0.628
job34	emp34	0.784	0.867	0.680	0.759
job35	emp35	0.688	0.733	0.680	0.694

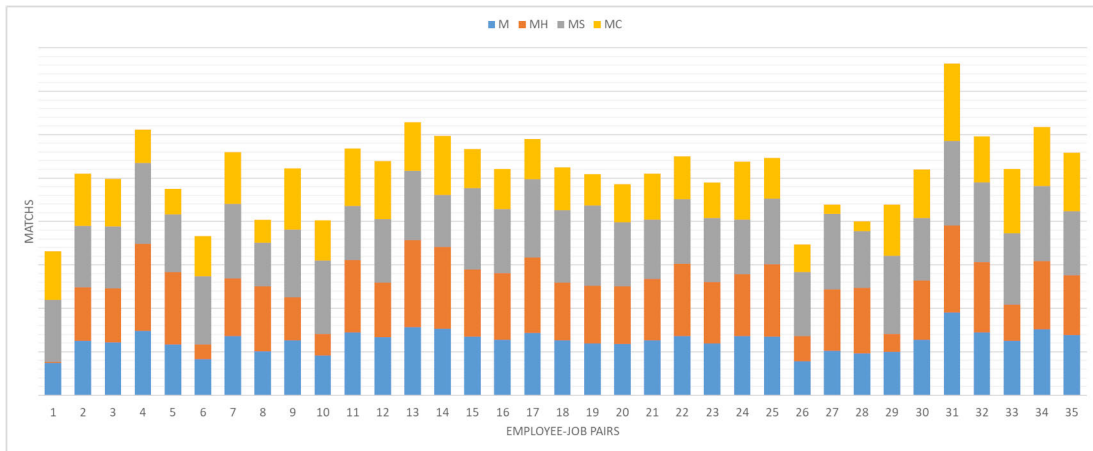


FIGURE 6. Global and partial degrees of satisfaction of assignments suggested by the proposed decision model.

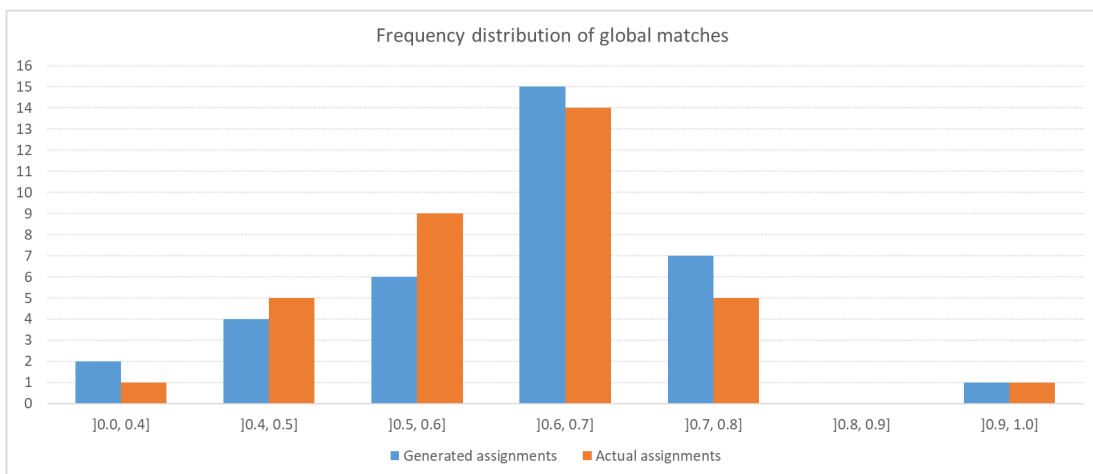


FIGURE 7. The comparison of frequency distribution of global matches for the generated (blue color) and actual (orange color) assignments.

B. ACTUAL ASSIGNMENTS

Results of the algorithm execution offered to HR managers a support for employees allocation. The decision was supported by assignment suggestions as well as all the other information acquired during the proof. 23 of 35 suggested assignments were accepted, thus about 66%.

However, the right to choose the actual allocation clearly remained to HR managers, who made 12 changes, with respect to the suggestions of the algorithm, associated with changes in terms of global matching (as calculated by the proposed decision model). Most of HR managers changes have been performed by manually choosing a different employee for some jobs, selecting them among those with higher degrees of mutual satisfaction with the jobs of interest, as computed by the decision models.

As a result, a decrease of 0.804 in the total matching degree can be calculated by comparing the choices of HR managers with respect to the suggested optimal allocation.

In detail, the actual allocation corresponds to a set of global degrees of satisfaction ranging from 0.246 to 0.952 (Mean \approx 0.604, SD \approx 0.127).

The resulting actual assignments with respective degrees of satisfaction is reported in Table 2, while the comparison of frequency distribution of global matches for the generated and actual assignments is shown in Figure 7. As a further measure of the method effectiveness, the Root Mean Squared Error of the set of global matches of the suggested allocations, with respect to those obtained by decision-maker is RMSE \approx 0.100.

C. DISCUSSION

The application of the proposed decision model produced valuable results.

First, the defined data model allowed to insert all descriptions, both at the employees and jobs sides, without any reported problem.

TABLE 2. The actual assignments after the decision-maker intervention (in bold the changes performed), the associated partial degrees of satisfaction of the preferences expressed by HR managers on employees (M^H and M^S) and by employees on jobs (M^C), and the global degree of satisfaction of such preferences (M).

Job	Employee	M^H	M^S	M^C	M
job01	emp15	0.013	0.807	0.587	0.401
job02	emp02	0.616	0.707	0.600	0.628
job03	emp06	0.008	0.680	0.267	0.246
job04	emp21	0.833	0.733	0.267	0.587
job05	emp05	0.833	0.667	0.293	0.584
job06	emp03	0.833	0.929	0.240	0.615
job07	emp07	0.667	0.857	0.600	0.678
job08	emp08	0.748	0.500	0.267	0.506
job09	emp09	0.493	0.778	0.707	0.635
job10	emp10	0.250	0.844	0.467	0.456
job11	emp11	0.833	0.618	0.667	0.724
job12	emp26	0.217	0.738	0.427	0.405
job13	emp13	1.000	0.800	0.560	0.784
job14	emp20	0.771	0.867	0.413	0.647
job15	emp01	0.521	0.933	0.307	0.518
job16	emp16	0.766	0.733	0.467	0.640
job17	emp17	0.870	0.900	0.467	0.714
job18	emp18	0.667	0.833	0.493	0.631
job19	emp19	0.667	0.922	0.360	0.595
job20	emp32	0.833	0.733	0.400	0.640
job21	emp04	0.583	0.589	0.400	0.511
job22	emp22	0.833	0.744	0.493	0.680
job23	emp23	0.708	0.733	0.413	0.595
job24	emp14	0.917	0.733	0.547	0.732
job25	emp25	0.833	0.760	0.467	0.672
job26	emp24	0.708	0.620	0.267	0.514
job27	emp27	0.708	0.867	0.113	0.510
job28	emp28	0.750	0.656	0.113	0.484
job29	emp29	0.208	0.900	0.587	0.498
job30	emp30	0.681	0.720	0.560	0.640
job31	emp31	1.000	0.973	0.893	0.952
job32	emp12	0.558	0.860	0.600	0.635
job33	emp33	0.413	0.820	0.747	0.628
job34	emp34	0.784	0.867	0.680	0.759
job35	emp35	0.688	0.733	0.680	0.694

Moreover, the algorithm execution allowed to individuate the best allocation, made of the set of employee-job pairs having matching degrees that, summed up, correspond to the maximum satisfaction of the whole Department. However, this could imply that, for some jobs (and for some employees), the best matching employee (job) was not chosen, and a sub-optimal choice was preferred by the algorithm, in order to ensure a better allocation of the whole set of employees and jobs.

HR managers accepted a good percentage of suggested associations. The reason why he accepted only partially the algorithm results, is probably due to the presence of some sub-optimal associations. Moreover, HR managers knew employees identities, which could lead to reasoning paths not encoded in the proposed decision model. Finally, HR managers could prefer to give more importance to the satisfaction of some job positions, while the proposed decision model involves equal weights in summing up the global matching degrees of all the employee-job pairs to calculate the total satisfaction. However, he produced actual assignments by just switching some positions; therefore, his effort was surely lowered by generated suggestions.

Moreover, he confirmed that he was undoubtedly helped by the information gathered during the experiment execution.

VI. CONCLUSION AND FUTURE WORK

This work aimed at supporting HR managers in the assignment of a number of newly hired employees to available job positions.

With this aim, a decision model was defined, which enables to analytically measure each employee-job pair goodness, based on weighted preferences of both employees and HR managers, and to apply AI to suggest the optimal allocation, made of the employee-job pairs gaining the maximum satisfaction of the whole department.

The case study, performed at the Italian Ministry of Economy and Finance, involved the customization of taxonomies used to insert useful information, the customization of weights, to tune the measure of goodness of employee-job pairs, and also presented privacy issues, simply solved by pseudonymization, and required to calculate anonymous statistics.

The experimental results proved the applicability of the proposed decision model, and its efficiency in suggesting the best allocation to HR managers, thus saving great human efforts.

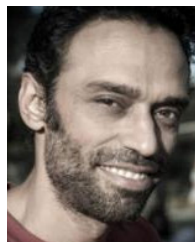
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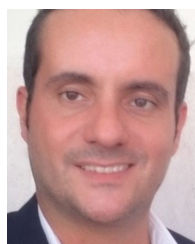
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