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How Graphs can Improve Targeting of Employee Trainings?

Zoltan Varadi
Óbuda University

Abstract: Skills matrices, also known as competency matrices, can help shift managers in a manufacturing environment in proper allocation of operators to workplaces. However, improving the skills portfolio of shift workers is often based on perceived problems with skills of absent workers. This study examines a company's skills matrices of the 3 shifts, questioning if graph metrics can help estimating substitutability, i.e., robustness of skills portfolio of workers to absenteeism; and how can graph mapping help better targeting trainings. The author has constructed bipartite graphs where one set of nodes are from the set of competencies and the other set of nodes are from the set of workers; and evaluated metrics comparing the skills portfolio of each shift. One projection of the bipartite graph shows the interlinks between people: when two workers are connected, they share the same skill and can substitute each other. The overall level of substitutability of people is then measured with the average degree of nodes of the projection graph. Weak connectedness, that is, low k values can highlight risks and exposedness to fallout of the respective workers. Disjoint graphs indicate if there is an option for a sub-team setup based on competencies. The other projection has an edge between to skills if and only if there is minimum one worker who is capable for both. Disjoint subgraphs of skills are helping team formation based on competencies.

Keywords: Skills matrix, Bipartite graph, Robustness, Substitutability, Team formation

Introduction

In mass production manufacturing environment, one of limiting factors is human resource, which's behaviour and capabilities change extremely rapidly, and external factors are unforeseenly altering its availability. If a worker falls out, the responsible leader, often the shift leader must immediately reallocate existing workers to maintain running of the facility. Reallocation decisions are supported not only by their experience, but useful tools such as competency matrices help to find sufficient replacement for the missing workers. Competency matrices help make sure that the substitutor is skilled and capable to perform the job. At the same time, shift leaders have juggle with capacities used for the moment and capacities of the future, thus ordering trainings to improve skill portfolio of workers. Those trainings are mostly done on the job (Patchong, 2016), and in working hours, the availability of the trainer is one of the driving forces. As a result, competency matrices are updated, skills are accumulated, but flexibility and exposedness to absenteeism is not examined in detail.

This study is questioning if the skills portfolio can be a good measure of substitutability, and contrary, the need for improving flexibility in immediate substitution of missing workers can determining training needs. A metric that estimates substitutability is developed on examining competences of high value adding indirect workers, where skills are not so rigidly standardized as in manufacturing. One of such metrics is the degree centrality of the human network (Szilágyi, 2019), with respect to the possessed competencies. Taking an industrial case study, the applicability of degree centrality as the measure of substitutability is evaluated, in case of competency matrices used in manufacturing environment.

The meanings of terms 'skill' and 'competency' are often differentiated, the former meaning the ability to apply knowledge, and the latter is possessing the knowledge and even some skills that leads to the ability to perform successfully (Torres, 2022). There are various definitions, in industrial practice they are quite often used as synonyms. The term competency matrix refers to a spreadsheet where names and needed skills are listed, and trainedness is indicated in the cells as illustrated in Figure 1. In this study, the two terms will not be differentiated, and the skills portfolio of workers will be denoted with the term competency matrix, as widely used in industry.

Method

A typical competency matrix can be interpreted as the adjacency matrix of a graph, where nodes are the row or column headings of the matrix. A non-empty cell in the matrix indicates a node: the employee in the row of the matrix is trained in the skill of the column, and in the graph, the node of the employee is connected to the node of the skill. Though skills matrices may have indication of the level of expertise, in this study we simplified it to two levels: if a cell of a matrix contains the value 1, that employee bears that skill; and if a cell is left empty then this employee is inexperienced in that selected skill (Figure 1.). Thus, edges in the graph will uniformly be weighted. The direction of nodes will have no meaning, so we set up an undirected graph. The elements of the adjacency matrix are then defined by equation (1):

$$a_{ij} = \begin{cases} 1 & \text{if employee } i \text{ is trained in skill } j \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

	Skill1	Skill2	Skill3	Skill4	Skill5	Skill6
Name1		1				
Name2	1					
Name3	1	1	1			
Name4			1			
Name5					1	1
Name6			1		1	1
Name7	1		1	1	1	
Name8			1	1		
Name9			1	1		1
Name10	1					
Name11	1			1	1	
Name12					1	1
Name13			1	1	1	
Name14						1
Name15	1		1			1

Figure 1. Illustration of a simplified skill matrix (own illustration)

The nodes form two disjoint sets: a set of nodes representing employees, and another set of nodes representing skills. Edges denote if a person is trained in the respective skill, thus every edge goes from a name to a skill (Figure 2.). Such a graph is called bipartite graph (Pokorádi, 2008). The diameter of dots representing the nodes on Figure 2 is proportional to the degree, i.e., the number of edges arriving at the respective node.

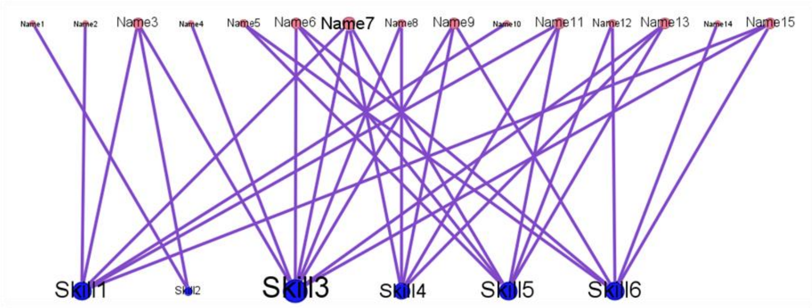

Figure 2. A names-skills bipartite graph generated from Figure 1. (own illustration)

In case a person is missing, e.g., on a sick leave or any other unplanned event, the shift leader can only choose another person to substitute the missing one, who shares the same skill. On the competency graph (Figure 2.), substitutability means two people can substitute each other in a job requiring a given skill if there is a path from Name(i) to Name(j), through Skill (n), as shown in equation (2). In this path, the hopcount equals exactly 2.

$$P_{Name(i)\to Name(j)}(2) = \text{Name}(i) \to \text{Skill}(s) \to \text{Name}(j) \tag{2}$$

Mapping substitutability means finding the two persons share the same skill, that is, listing each path between names where the hopcount equals 2 exactly. A projection (Barabási, 2016) of the names-skills bipartite graph (Figure 2.) to the nodes of names would result in a graph where between two names there is only an edge when they share a skill. If they share several skills, the edge weight equals the number of skills they both possess. Let ${}_Na_{ij}$ denote the elements of the adjacency matrix of the Names projection of the names-skills bipartite graph, and its values are then given by equation (3).

$${}_Na_{ij} = \begin{cases} c_{ij} & \text{where } c_{ij} \text{ is the count of skills } Name(i) \text{ and } Name(j) \text{ have in common} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

A very similar projection of the names-skills bipartite graph is available for the skills. If two skills are connected with an edge on that projection, it means there are people who share those skills and can substitute each other in the other skill. If we assume that one skill is needed to perform a given job and another skill is needed to perform another job, this projection identifies the possibility to reallocate people from one job to another in case there is insufficient number of workers in a job, and load and priorities makes reallocation possible. Gephi Graph Visualization and Manipulation Software ver.0.10.1. has been used to plot and analyze graphs, and projections were filtered with the MultiMode Networks Transformation Plugin. The bipartite graph of Figure 2 is then simplified to the following projections (Figure 3. and 4.):

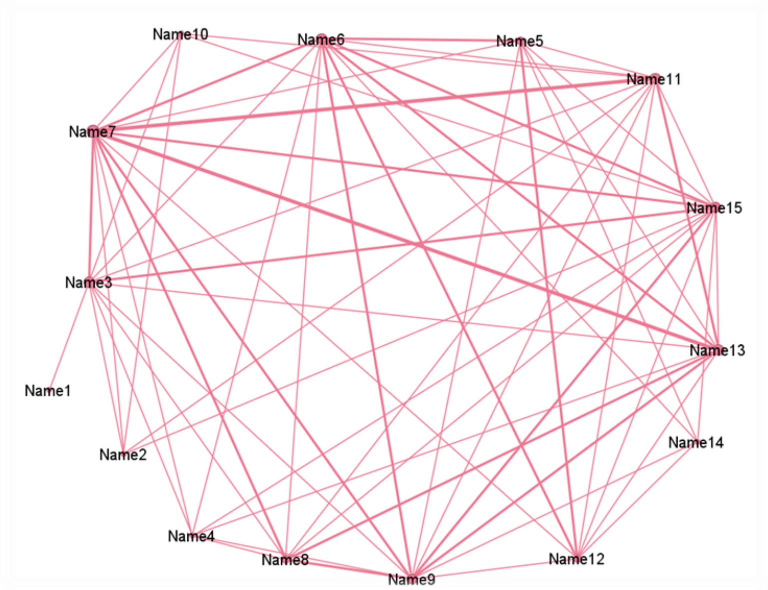

Figure 3. The names projection from graph of Figure 2. (own illustration)

If a person has only one connection, that means he has only one other person with whom they can substitute each other in case either one is missing from the job, like 'Name 1' and 'Name 3' on Figure 3. The number of connections, i.e., the degree of a given node sets a pool of people who can substitute in case a person is missing. If 'Name 1' falls out, 'Name 3' is there to substitute him or her on the skill they have in common; and as the weight of this connection is 1, they share only one skill. On the other hand, if 'Name 3' falls out, his or her connections define the pool of various other people who can substitute him or her, but we have to keep in mind that 'Name 3' had 3 skills and is capable to work in various positions. On a given day, the shiftleader will need to substitute 'Name 3' only in a particular job requiring a specific skill, thus, limiting the pool to those people who share the required skill with 'Name 3'.

In this study, we work with the simplification that one given job requires a given skill, and do not examine the strategic importance and load of jobs. To keep the privacy of the data provider, skills are indicated by numbers such as 'Skill1' to 'Skill70', and so are people identified with 'Name1', et cetera. Functional areas and groups of technology are numbered, and shifts are marked with capital letters in the analysis.

The greater number of skills two people share, i.e., the larger the weight of an edge connecting them, the more jobs they can substitute each other. The most optimistic, yet unrealistic approach is to arrive at a complete graph on both projections, with uniform weight distribution, i.e., every single person can substitute anybody else in any selected job. A complete graph has a density equals 1, that means each node is connected to each of its possible neighbors (Barabási, 2016).

Weights of edges on the skills projection indicate how many people share the two skills, that is, the number of people who are skilled to do both of the jobs. If a skill is disconnected, the people bearing that skill can not be redeployed in other jobs requiring other skills, thus reducing flexibility on allocation. Missing or weak links between skills may indicate the need of cross-functional training of workers, and so improving reallocation possibilities.

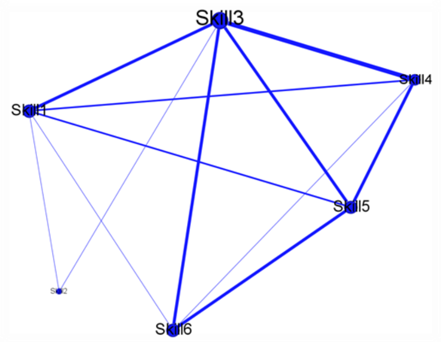

Figure 4. The skills projection from graph of Figure 2. (own illustration)

Data Source

An electronics manufacturer company’s plant located in Central Hungary region provided competency matrices of the direct production areas. At the time of study, 447 workers allocated in 3 shift work pattern were analyzed, and 70 skills identified so that a skill is required to perform a job. During cleaning of the data, we found new recruits who are not yet trained sufficiently in any of the skills, and not capable to work alone in any of the jobs. These newcomers with zero skills are excluded from the further analyses, as they have zero links in the names-skills bipartite graph, cannot substitute any other operator, and cannot be substituted by anyone else.

Substitutability of fallen-out workers is a short-term problem for shiftleaders, as they must redeploy people in the beginning of the shift in order to enable running most of the workstations according to the production schedule. At that very point of time, they cannot rely on workers of other shifts as they are away from the plant and are unreachable for the duration of their compulsory rest periods. Immediate substitutability is just served by the people who are in at the given shift, with the skills portfolio they have been trained in the past. Thus, shifts A, B, and C are separately analyzed and compared. Headcounts of shifts allocated to the functional areas is summarized below (Table 1.):

Table 1. Headcount distribution pivoted from the competency matrices.

Shift → Functional area	A	B	C
1	14	15	14
2	16	20	16
3	17	14	15
4	25	28	18
5	13	16	13
6	28	27	24
7	39	40	35
Total	152	160	135

The manufacturing area has a functional layout, that means, similar technologies are located nearby, so are similar job positions geographically near each other on the shopfloor. Supervisors of the seven functional areas are supported with trainers who work as power users, train newcomers, and cross-train existing workers to new skills in their standard working hours. Functional areas are within the same building just a few steps away from each other, however, cross cooperation of trainers is hardly observed.

Results and Discussion

Descriptive Analysis

In the competency matrices, there are altogether 2416 records of trainedness for the 447 people, averaging out to 5.4 skills per person, that means, an average worker is able to perform 5 different jobs. The distribution of skills count per person surprisingly shows (Figure 5), there are workers possessing more than 20% of all the skills needed in the factory. Their overtrainedness is hardly justified by business needs, in addition, it is unlikely that one person can perform 16 different jobs at the same quality. There is a visible difference between shifts with regards to the distribution of skill count per person, suggesting that the three shiftleaders and their trainers by functional areas might run their own procedures on selecting whom to train and to what to train. In shift B, the 17 people having 0 skills are seemingly newcomers already included in the matrix but not yet able to work alone in any of the jobs.

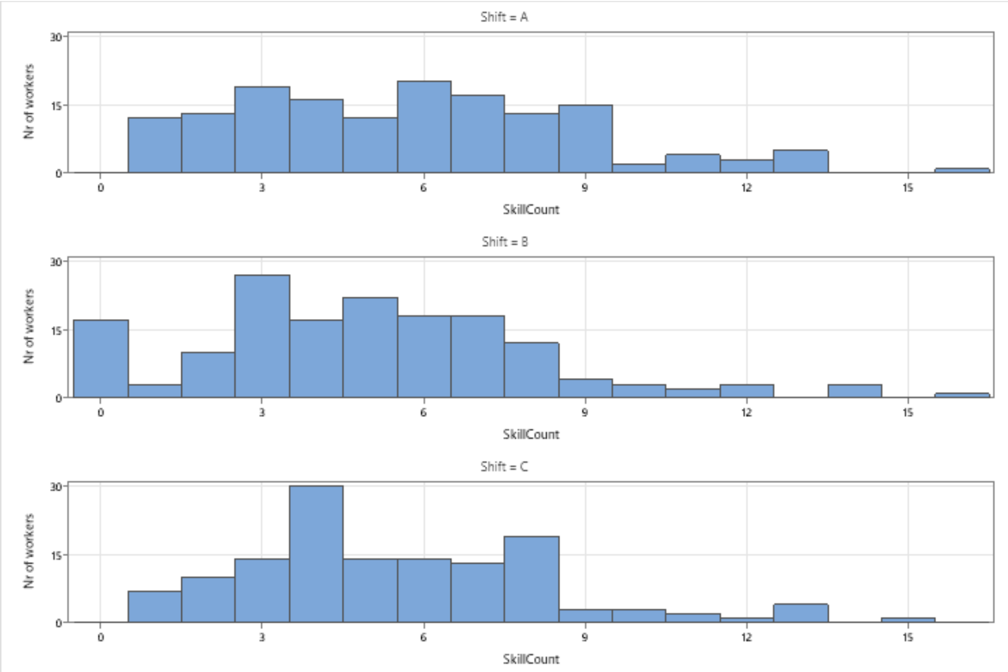

Figure 5. The number of skills workers possess, by shift. (own diagram)

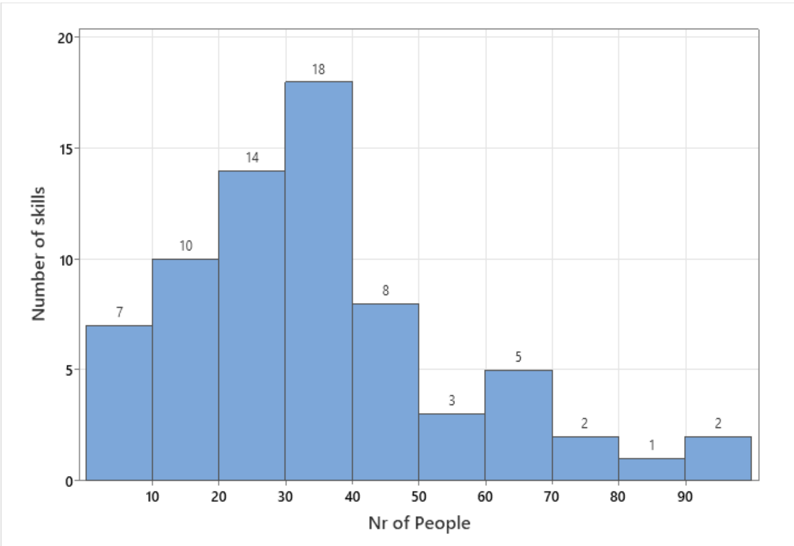

Figure 6. The number of skills by the number of people possessing them. (own diagram)

The penetration of trainings can also be measured from the skills point of view (Figure 6.) There are only 7 skills at which less than 10 people are trained plant-wide, that is 10% of all the skills. Speaking substitutability point of view, these are the skills with highest training priority, unless these were associated with jobs ramping down. On the other end of the scale, there are 3 skills which are possessed by more than 20% of the workers. Overrepresentation may be justified if those skills were basic skills of strategic importance, or they were associated with jobs performed by large number of people in a parallel arrangement, due to reasons of capacity adjustment.

Outcomes of Bipartite Graphs

Bipartite graphs of names and skills have been constructed for each shifts' competency matrices, and colors were assigned to identify functional areas, meaning the same functional areas throughout all the graphs, as follows: red – 1; violet – 2; blue – 3; light blue – 4; green – 5; melon – 6; brown – 7. Projections of the graphs (Figure 7.) were created by MultiMode Networks Transformation Plugin of Gephi, and visualization was rendered with Fruchterman Reingold algorithm (Fruchterman & Reingold, 1991) of Gephi (Heymann, 2015).

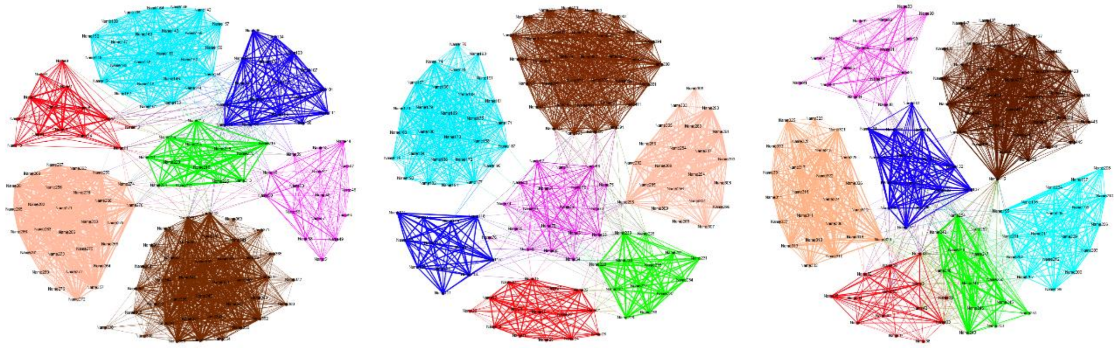

Figure 7. Projection to people of shifts A, B and C respectively (own graph)

Projections to people indicate that within functional areas there are strong connections of people, i.e., they share the same skills, but, apart from a few bridges, they can not be redeployed in any other area. Quantitative description of projections and their subgraphs filtered to functional areas is summarized in Table 2. Although average degrees are high above 20 suggesting good choice of substitutability for replacing a missing person, they do not seem to ensure flexibility of reallocation, because nodes only have high degrees with nodes within the same functional area. If we filter to edges which connect nodes between functional areas, the average degree drops dramatically to 1.5-3.5. The quantitative analysis supports the visual impression of Figure 7, that the factory has nearly full flexibility of substitution within any functional areas; but there are hardly any people who could relocate to another cell in case they are needed elsewhere.

Table 2. Quantitative description of projections and subgraphs.

Functional area	Density			Average degree		
	A	B	C	A	B	C
1	0.967	0.962	0.934	12.571	13.467	12.143
2	1	0.906	0.917	15	16.316	13.750
3	1	1	1	16	11	14
4	1	0.995	1	24	26.857	17
5	1	1	1	12	12	12
6	0.992	1	1	26.786	21	23
7	0.911	1	0.992	34.615	33	33.714
Total graph	0.167	0.165	0.181	25.250	23.427	24.222
Between functional areas	0.013	0.011	0.026	1.934	1.497	3.526

It is not a surprise that skills are more tied to the functional areas, however, a very similar phenomena are visible on the projections to skills (Figure 8.), mostly skills within the same functional area share a substantial number of people, whereas there are very few connections between functional areas. There are disconnected nodes on the skills projection in every shift: only 1 in shifts 'A' and 'B', and 7 in shift 'C' – suggesting that shift 'C' organizes and documents shopfloor trainings on a different manner. People who work in jobs where disconnected skills are required have no substitute people in case they fall out of work, that brings a huge risk to business continuity.

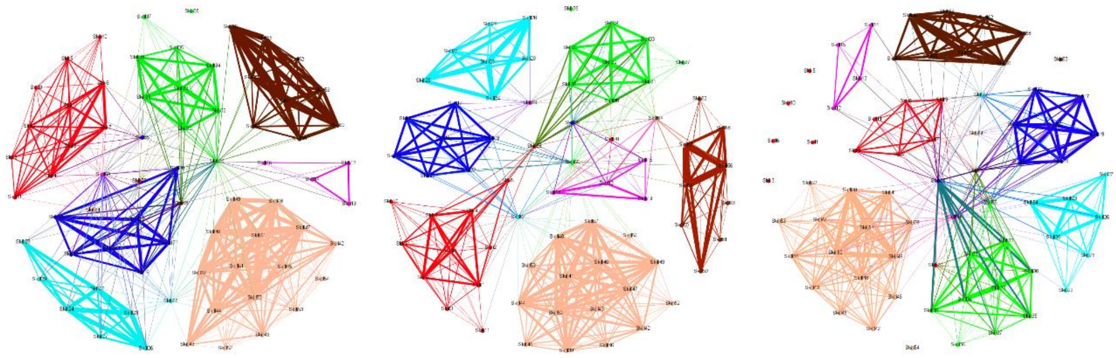

Figure 8. Projection to skills of shifts A, B and C respectively (own graph)

Our expected outcome was to find interrelated skills on that projection, which enable us to form clusters of skills for trainings. Figure 8. suggests the existence of such clusters, however, in the case of the examined company, these clusters existed before the analysis. The functional arrangement of layout and the trainers assigned to area supervisors directs trainers to focus only on their own area's required skills. In this company, the local focus went so far that it practically disables redeploying people in another areas as they are trained to be specialists of their own area.

Conclusion

A bipartite graph can be constructed taking a competency matrix as its adjacency matrix, and having one set of nodes as the workers, and the other set of nodes as skills or competencies. There is an edge between a person and a skill if and only if the person possesses that skill. Projections of that bipartite graph to people has an edge between two persons if and only if they share a skill, that is, in case any of them falls out, the other person can substitute him or her on that skill. The degree of a node indicates how many people are potentially capable to substitute that person represented by a node, on the skill they both share.

This study was aiming to use the degree centrality to measure the level of substitutability. By finding the nodes with the lowest degree, i.e., the least replaceable people, and implementing training programs to cross-learn each other's skills would improve the degree distribution. The analyzed data set however showed it, that degree centrality by itself is not sufficient to measure substitutability, as the projection graph had clearly visible clusters aligned with functional groups. The average degree within clusters was a magnitude higher than the degree between clusters, thus showing that substitution is possible within a cluster, but the flexibility of reallocation is limited across functional areas. A possible explanation of such an imbalance could result from the functional arrangement: if a newcomer is first introduced to an area and learns its skills, becomes familiar with machines and people working in that micro-environment, later neither the worker wants to move on, nor the area supervisors are willing to lose a trained person, eventually, the employee is trapped in that area.

The density of the projection graph may be another indicator of substitutability. If the density is close to 1, practically any employee may replace anybody else, as they all pairwise share a skill or more. Density equals or is close to 1 in subgraphs filtered to functional areas. The practical guide to the shiftleader in that case would read like: if there is a lacking person, try to find replacement within the same functional area.

Recommendations

If there is a business need to improve allocation flexibility – as it was at the data source company, the competency portfolio shall be developed with cross-functional trainings, that is, trainings shall not stay within one area. In terms of density of the names projection of the names-skills competency graph, that mean more homogeneous density distribution.

Substitutability in manufacturing environment where necessary skills are standardized is a field yet to study. With It is an open research question if there is a limiting density, above which business continuity is not in risk.

The author recommends to further analyze the robustness of the human network of manufacturing based on skills portfolio and find if there is correlation between the absenteeism rate and the limiting density.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the author.

Acknowledgements or Notes

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Author Information

Zoltán Váradi
Óbuda University,
Budapest, Hungary
Contact e-mail: *varadi.zoltan@kgk.uni-obuda.hu*

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