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# Mathematical Method for Selecting Team Members from a Social Network

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***ABSTRACT:*** Selecting the most effective team from a social network has two different viewpoints. The team should be connected together in a proper way to enable co-operation. In addition, the individuals should have needed skills to complete the task. The selection problem arises from optimizing the combination of these two aspects. In this paper, a modelling method is described for a situation where specific skills are required for different tasks in the project. A typical issue in organizing a project team is insufficient analysis of existing social relationships between the potential team members. The relationships are either regarded as strict command relationships or less strict support relationships. However, there are aspects of social networking that are usually left unnoticed. The better the potential team members know each other the better the selected members are expected to interact in collaboration situations. Often, these kinds of relationships can be observed in social media connections. The methods in this paper can be used for selecting team members from a social network in many organizational situations. A novelty in this paper is to consider also connections of the team members with a social network around the team. In addition, we discuss features concerning the special case of selecting members for a military task force. This highlights some issues, for example, the selection of a manager for the team.

***KEYWORDS:*** social network, team effectiveness, selecting team members, team network, external social network

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## I. INTRODUCTION

A current trend in both business and public organizations is turning towards more dynamic, project-oriented team-building, based on current or near-future needs [29]. Solid hierarchical organizations have a role in a stable environment, where processes, their inputs and outputs as well as the overall effects towards the organization are more or less known. As the competition between businesses and public organizations, even nations, grows, strategic advantage may be gained by optimizing the organization's capability to "get the task done" and by focusing on core business. In this volatile environment, there have been some attempts to solve the issue between the solid, well-defined, managed and very organic, self-organizing organizations. A typical solution is the matrix organization, where vertical relationships represent hierarchical relationships between sub-organizations and horizontal relationships either common functions (ICT, HR etc.) or business segments (customer accounts etc.). In a more granular level of management, projects and project organizations come into play. When the organization is seen mostly as a pool of resources for core business projects, project resource management becomes the main function of the organization. The major task is to optimize the usage of current staff to provide the maximum profit (or, in a public service, maximum output for taxpayers' money). In such a situation, ability to build teams effectively is essential. In team-building, the entire organization can be seen as a resource pool, from which the optimal team is derived.

Certainly, the reality is not that simple. All of these structures may exist simultaneously inside the organization, not only as explicit well-defined relationships but in different kinds of social networks. Ultimately, even friendship and family relationships can be seen as networks inside the organization. These social networks are realized in several ways [5].

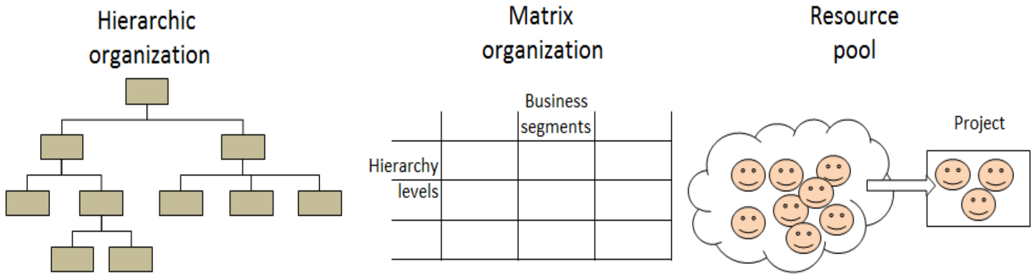


**Fig.1:** Hierarchical vs. matrix vs. resource pool approaches to organization structures.

In the military context, the previous elements apply as well. The trend towards a more fast-paced environment, where task forces cannot be planned beforehand, but have to be formed ad hoc, is evident [16]. Asymmetric warfare is based on events, where an opposing force, small in numbers, can build up task groups, act swiftly and change behaviour, organization, and targets in such a manner that a more rigorous opponent cannot follow it. On the other hand, such a volatile organization does not have the same effectiveness in routine work than a well-defined organization with its pre-defined processes.

The basic organization in the military context is a hierarchical structure. The task forces are formed by commanding a task leader and assigning needed supporting elements around the nucleus task group. While this may be an effective method for creating task forces, it becomes cumbersome in situations, where the number of task forces becomes higher. From this point of view the hierarchical relationships can be seen more as an initial setting for the entire organization, which is actually just a resource pool for the task force's actual mission elements. In the military context, organizing a task force for a mission is a critical function. In ad hoc situations, both the time to create the task force and the resulting group's effectiveness are the main issues. To support the decision-making in an ad hoc situation, some analytical support is needed.

An essential factor in the modern world is social networking of potential team members. The rise of the Internet has provided us with several services to network and collaborate effectively with our co-workers. The service used in each situation may depend on the Community of Interest and its (sometimes arbitrarily) chosen methods, or a strict need for a certain type of function, like the security service. These social networks typically overlap and change over time due to personal changes in professional careers, relationships, hobbies, and the evolution of social networking technologies.

The methodology of agile team-building has been discussed widely and several approaches have been presented. In an operative environment, there are some routines, which try to optimize the abovementioned balance between rigorousness/effectiveness and ability to take into account also unexpected or uniformalised issues. In many cases, the planning process is well-defined [50], but several options are typically presented to the team leader. In this way the intuition based on experience, training and surrounding "fuzzy factors" can be taken into account.

The analytical approach of this paper serves as a basis for decision-making in the team-building process. The idea is to provide the team leader with options which have their basis in the analytical approach. The best (typically three) options can then be presented as an input for decision-making in the team-building process. Thus the process becomes faster by pre-selection of the most plausible team candidates, while the team leader has still the option to select the detailed team composition for the task.

## II. Related Studies On Social Networks' Impact On Team Performance

There are several research articles concerning the impact of social network features and organizational structure on team performance. Teams are embedded in structured knowledge networks interacting internally and externally with the aim of accomplishing a common task [48]. Team members exert their social influence, change opinions, and converge to a common understanding. People benefit from advantageous network positions that provide access to useful knowledge, career sponsorship, and psychological support [15].

In their article [48] study how social network features and organizational structure impact team performance in uncertain environments. High-density values of the team knowledge network are beneficial in the majority of cases, but may become detrimental, when the uncertainty of the environment is low, the network exhibits a random connectivity, and strong leadership behaviour. These are very special cases, where social networking may not enhance the performance of teams, which don't describe a typical environment considered in this paper.

Based on the extensive literature on social structures and team performance [10], [13], [14], [18], [20], [21], [41], [46], [47], advantageous effects of positive social interactions and social networking on team performance [2], [6], [8], [11], [15], [24], [38], [42], [44], [45] are regarded as a baseline fact in this paper.

## III. GENERAL METHOD OF COMPUTING INFLUENCE MEASURE OF SOCIAL NETWORKS

Selecting the optimal team is a common problem in almost all fields of business and in public organizations. Often, the main focus is on final outputs produced by the team. Essential to achieve this is team's ability to work together through internal social processes between the team members. Associated with internal social processes are external social interactions through social networking with people outside the team. These interactions enhance learning and the group's ability to work together in the future [36]. Moreover, collecting together a Community of Interest (COI in the military context) network provides a valuable tool for project team formation process [7], [12], [17], [19], [32]–[35].

**The basic problems for this process can be divided as follows:**

- Which members of the (networked) group are potential team member candidates for the project group or Community of Interest?
- How can we use social networking as an internal (project or Community of Interest) and external (overall network) factor to evaluate the individuals and their suitability as team members?
- How can we combine social networking and personal skills to estimate the overall suitability of an individual to the team?
- How do we use time as a factor?

In this paper, we propose a mathematical method [27], [28] and algorithm to compute the optimal composition of the team selected from a social network structure. A quantitative measure can be computed for all the possible alternatives of the team structure describing effectiveness of a social network. One member of the group can be appointed as a manager, and the effectiveness measure can be used to compare, which candidates build up the most effective teams. If the team is self-managed, the effectiveness measure is computed as an average value of all the individual members acting, in turn, as the group leader. The optimally managed and non-managed teams may be composed of different members depending on the internal and external structure of the network.

The main results of this paper consider the selection of the most effective social networking structure between the team members as part of a networking environment. In a case, when all the group members perform the same tasks, the effectiveness measure is computed for the network structure, including internal and external ties of the team. This is combined with a second factor describing the ability of the members to perform the tasks. This procedure takes into account both social interactions [3], [19], [32], [33], [35], [39], [40] and individual skills of the group members. Usually the abilities of the member candidates to perform the tasks are known before computing the effectiveness measures for different compositions of the team. In a more complex situation, the weighting factors can depend on the actual choice of other team members.

The method is scalable for small networks typically investigated in scientific papers, for example in [1] and [30]. The aim of this paper is to present the mathematical method while the efficiency and scalability of the computer program is discussed in a recent work [25]. In approximate computations of large social networks, the well-known rule of "six degrees" [49] allows us to include only connections between nodes with limited path lengths. In addition to this restriction, ability to work together, personal skills and suitability is a complex issue. While a general solution is presented in the methodology section (Section III) particular factors and their dependencies of time etc. are too case specific to be presented in this paper.

There are many methods for evaluating importance of nodes as influence, information and rumour spreaders (See Section II.). Degree centrality, betweenness centrality and closeness centrality are the measures commonly used in social network analysis [4]. Many variations of these measures exist and some of them have lower computational complexity than others [30], [25].

Most of the influence measures presented in the literature lack exact definitions of the context of use and quantitative interpretation. This paper proposes an exact closed form mathematical method that has the quantitative interpretation as the probability of influence spreading. This method is proposed for a reference theory to be used in comparing various qualitative or approximate social influence measures. Important variables of the method are: size of the team, time (the development phase of the influence spreading process) and node activities [28] inside and outside the team.

The methodology is presented in the following way: first, the mathematical method of computing influence measures of social networks is presented [27], [28]. Next, the method of computing team effectiveness originating from social networking capabilities and practical skills is described (Section IV). In the same section a temporal spreading model together with the role of node activities are discussed. In the next section (Section V), the aspects in selecting a team from a network and relations of the team members with the remaining larger social network are covered. Finally, the method is demonstrated (Section VI) with social relations among Renaissance Florentine families [22]. The application to a real (present-day) social network data is presented in Section VII. The same social network structure has been analysed from a general point of view also in [28].

The effectiveness of the team, whose members are selected from a network structure, is computed with the help of general methods and ideas used in the social network theory [1], [4], [7], [9], [23], [31], [34], [37], [43]. The algorithm proposed in this paper relies on listing all the possible paths in the network and computing the contribution of the paths in the social network structure in an exact closed form. It is essential to consider the paths as being not independent because different paths have common links. In this model, only the common links at the beginning of the paths from a source node to a target node must be considered. If common links appear later, that is, the paths combine together, they are regarded independent. In other words, we assume that the initial source node or intermediate nodes are not recorded (no memory) or not taken into account by the node in the network when the influence is intermediated via different paths.

We demonstrate the method with the social network structure in Fig. 2 [22]. The network topology describes social relations among Renaissance Florentine families. Albeit, the method can be used for larger social networks, the small network of Fig. 2 is appropriate for illustrating the method and mathematical formulas of the theory.

As we consider the team as a sub-group of a network structure, we construct the mathematical formulas for the complete network of Fig. 2. The selected team members, for example four nodes, of the network get higher weighting factors (these weighting factors can be different for the individual members of the team). The other nodes outside the team have lower weighting factors (again these can be different for individual nodes). The interpretation is that the team's internal connections are strengthened and external connections are weakened when the team is created.

In Table 1 all the paths from Node 1 to Node 2 of Fig. 2 are listed together with path lengths and number of common links (path lengths) at the beginning of paths compared to the preceding path in the list. The paths are ordered in descending order of common path lengths. We need to describe the algorithm only for one pair of nodes because the paths are assumed to be independent for different pairs of nodes in the network. The same idea is applied to all the pairs of nodes. The column "common path length" is the key information in the algorithm because we execute the computation in descending order of the value shown in the column. For example, in line 1-8-10-11-6-7-5-9-2, the common path length with the previous path 1-8-10-11-6-2 is four. The common path is 1-8-10-11-6 at the beginning of both paths.

In Table 1 the five steps needed to compute the social influence from Node 1 to Node 2 is indicated with Roman numbers I, II, …, V. Note that the number of steps may vary between different pairs of nodes in the network. Also, the four independent branches of connections in the table are indicated with grey color. These branches can be seen in Fig. 2 as four different independent links starting form Node 1 to Node 2. They are links 1-3, 1-5, 1-8, and 1-9.

We denote the probability of influence spreading in one time unit by $P_i$ where $i$ is the length of the path from a source node to a target node. Later, we discuss the features of the theory when probabilities depend on individual nodes in the paths. In this section we don't indicate these weighting factors explicitly in formulas. But indeed, we could use the notation in Equation (1) $P_5$=$P_5$(1-8-10-11-6-2). To be precise, we assume that a source node has full influence on all the neighbouring nodes – in $P_5$ Node 1 has the probability value 1.0 of influence.

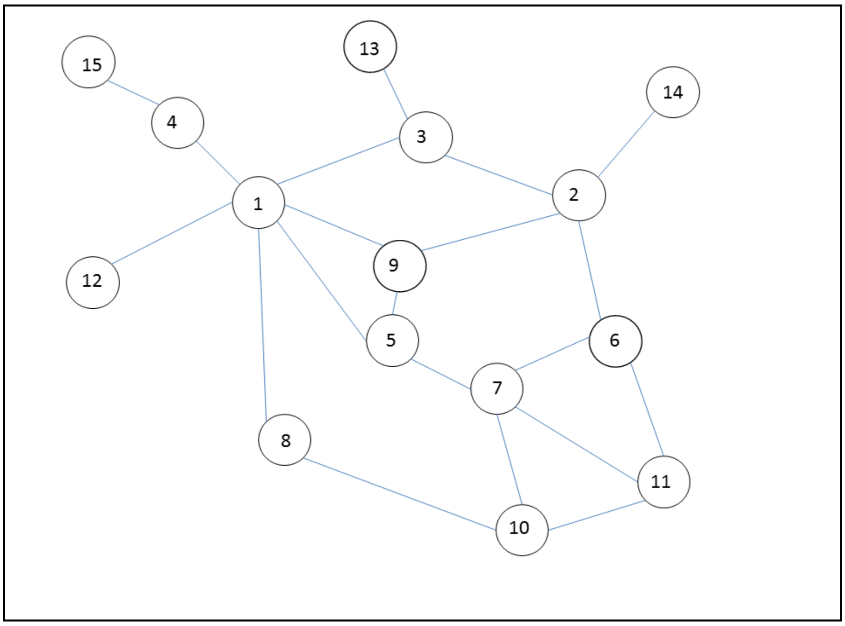


**Fig. 2.** Social relations among Renaissance Florentine families [22].

**Table 1.** This example illustrates the general computer algorithm explained in the text. All the paths from Node 1 to Node 2 of Fig. 2 with path lengths and common path lengths compared to previous paths in the list. Steps I, II, III, IV, and V indicate the order of computing the social influence of Node 1 on Node 2.

| path | length | common path length | I | II | III | IV | V |
|---|---|---|---|---|---|---|---|
| 1-3-2 | 2 | 0 | | | | | *8* |
| 1-5-7-6-2 | 4 | 0 | | | *4* | *6* | |
| 1-5-7-10-11-6-2 | 6 | 2 | | | | | |
| 1-5-9-2 | 3 | 1 | | | | | |
| 1-8-10-7-5-9-2 | 6 | 0 | | *2* | *5* | | |
| 1-8-10-7-6-2 | 5 | 3 | | | | | |
| 1-8-10-11-6-2 | 5 | 2 | *1* | | | | |
| 1-8-10-11-6-7-5-9-2 | 8 | 4 | | | | | |
| 1-9-2 | 2 | 0 | | | | *7* | |
| 1-9-5-7-6-2 | 5 | 1 | | *3* | | | |
| 1-9-5-7-10-11-6-2 | 7 | 3 | | | | | |

Next, we execute the algorithm starting from Step I in Table 1. In combining the paths 1-8-10-11-6-2 and 1-8-10-11-6-7-5-9-2 we join together the paths with common paths of length 4. In the following, we use the short hand notations $C_4$=1-8-10-11-6, $B_1$=6-2, and $B_4$=6-7-5-9-2 and denote the conditional probabilities by $P_1(B1|C4)$ and $P_4(B_4|C_4)$. The justification for Equation (1) follows from the following probabilistic formula:

$$P_{(1)} = P_4(C_4)[P_1(B_1 | C_4) + P_4(B_4 | C_4) - P_1(B_1 | C_4)P_4(B_4 | C_4)] = P_4(C_4)P_1(B_1 | C_4) + P_4(C_4)P_4(B_4 | C_4) - \frac{P_4(C_4)P_1(B_1 | C_4)P_4(C_4)P_4(B_4 | C_4)}{P_4(C_4)}.$$

It follows that

$$P_{(1)} = P_5 + P_8 - \frac{P_5P_8}{P_4}. \tag{1}$$

This principle is used repeatedly in the following equations. In Step II we combine the paths with common paths of length 3:

$$P_{(2)} = P_5 + P_6 - \frac{P_5P_6}{P_3} \text{ and} \tag{2}$$

$$P_{(3)} = P_5 + P_7 - \frac{P_5P_7}{P_3}. \tag{3}$$

In Step III we combine the paths with common paths of length 2:

$$P_{(4)} = P_4 + P_6 - \frac{P_4P_6}{P_2} \text{ and} \tag{4}$$

$$P_{(5)} = P_{(1)} + P_{(2)} - \frac{P_{(1)}P_{(2)}}{P_2}. \tag{5}$$

In Step IV we combine the paths with common paths of length 1:

$$P_{(6)} = P_{(4)} + P_3 - \frac{P_{(4)}P_3}{P_1} \text{ and} \tag{6}$$

$$P_{(7)} = P_2 + P_{(3)} - \frac{P_2P_{(3)}}{P_1}. \tag{7}$$

The algorithm is executed in descending order of the values of common path lengths [27], [28]. The path 1-3-2 has no common paths with the other paths from Node 1 to Node 2. Finally in Step V all the four independent branches are combined:

$$\begin{aligned} P &= 1-(1-P_1)(1-P_{(6)})(1-P_{(5)})(1-P_{(7)}) = P_1 + P_{(6)} + P_{(5)} + P_{(7)} - \\ &P_1P_{(6)} - P_1P_{(5)} - P_1P_{(7)} - P_{(6)}P_{(5)} - P_{(6)}P_{(7)} - P_{(5)}P_{(7)} + P_1P_{(6)}P_{(5)} + P_{(6)}P_{(5)}P_{(7)} + P_1P_{(5)}P_{(7)} + P_1P_{(6)}P_{(7)} - \\ &P_1P_{(6)}P_{(5)}P_{(7)}. \end{aligned} \tag{8}$$

## IV. THE METHOD OF COMPUTING TEAM EFFECTIVENESS

In Table 1 all the paths from Node 1 to Node 2 and the nodes belonging to the paths are shown. Because of the detailed structure of the model, the individual weighting factors describing the strengths of the nodes can be introduced in the model. In the previous section, individual node characteristics were not considered. Another possibility is to use weighting factors for the links of a network, but we have not chosen this approach in this paper. Weighting factors describe the activity of nodes in the network as influence spreaders. The weighting factors, i.e. the activities, depend on the issue at hand. Appropriate weighting factors should be used, if available, and in cases where very diverse tasks are given to the team, possibly different weighting factors should be used for different tasks.

In the basic case, we assume that team effectiveness ($P_{Total}$) can be expressed as a product of two factors: the effectiveness of social networking ($P_{SN}$) in the group and the effectiveness to execute the task ($P_{Task}$):

$$P_{Total} = P_{SN} P_{Task} \,. \tag{9}$$

The first term $P_{SN}$ in Equation (9) was denoted by $P$ in the previous section in Equation (8).

Obviously, our goal is to optimize $P_{Total}$ in Equation (9), not just $P_{SN}$ or $P_{Task}$. Because all the quantities are expressed as probabilities, no extra normalization or phenomenological adjusting is needed in the equations. Equation (9) is understandable in a situation, where the team is performing only one task or very similar tasks. In more complex cases, where different skills are needed in several tasks Equation (9) is not satisfactory. More detailed modelling is required to describe the interrelations of different tasks given to the team. This can be accomplished by considering every task as a part of the overall project plan of the team. The project is composed of obligatory tasks and alternative tasks. Correspondingly, these can be modeled as serial and parallel components with probabilistic terms. For example, if tasks A and B are obligatory and task C is an alternative way of executing task B, we have:

$$P_{total} = P_{SN,A} P_{Task,A} (P_{SN,B} P_{Task,B} + P_{SN,C} P_{Task,C} - P_{SN,B} P_{Task,B} P_{SN,C} P_{Task,C}) \tag{10}$$

This simple example demonstrates the idea that can be extended to a higher number of different (or similar) tasks. It is noticeable that the effectiveness of different social networking in the group may also vary from task to task. The weighting factors describing the activity of the team members or even the structure of the network can be different.

In Equation (10), the probability of finishing task X is denoted by $P_{Task,X}$. The granularity of the equation may not be detailed enough. In some cases, the modelling should be at personal level, taking into account the individual skills of the team members. The quantities $P_{Task,X}$ should be described at the lowest level of sub-tasks $P_{Sub\text{-}Task,X}$. At this level, one sub-task corresponds one member of the team. Again, this decomposition into smaller sub-tasks can be conducted with the same principles as in Equation (10) and possibly several levels of hierarchy are necessary to achieve the desired accuracy of modelling.

Next, we investigate the social networking effectiveness PSN in more detail. In the previous section, we assumed implicitly a fixed development time of influence spreading in the network. If the term “spreading” is used, the concept of time must also be included in the model. The source node is the initiator of the social influence process in the network. The model enables also several nodes to act in parallel as source nodes. Parallel source nodes are assumed to act independently which makes the computations straightforward (technically, weighting factors less than 1.0 for the initiators may be used to avoid bias in the normalization of probabilistic quantities).

First, the spreading process from a source node to a target node is considered on a chain network where nodes are connected in a simple linear structure without branching paths. In a chain network, a temporal distribution law of the spreading from a source node to its neighbouring nodes and from neighbouring nodes forward is needed. The choice between different distribution models depends on the problem. After all, we have found out that Poisson distribution and uniform distribution in a time unit [28], for example, with appropriate distribution parameters give almost the same influence spreading results in social networks. Assuming the Poisson distribution the probability of at least $k$ events occurring is:

$$P_k = P\big(K(t) \geq k\big) = 1 - \sum_{I=0}^{k-1} e^{-\lambda t} \frac{(\lambda t)^I}{I!}, \big(P_0 = 1\big) \tag{11}$$

Here, the interpretation is that the spreading has advanced k or more links in the network at time t. The intensity parameter of Poisson distribution is denoted by $\lambda$. The statistical distribution and its parameters determine the spreading rate in the network. The result of Equation (11) is identified as unconditional probability $P_k$ in the previous section.

Now, a question arises, which time value $t$ to choose for the computations. For this, two aspects should be taken into account. First, there is an equilibrium state of the spreading process when time $t$ is approaching infinity. Secondly, if the nodes' activity is not full 100 % the probabilities $P_k$ approach values less than 1.0 in the equilibrium. If the activities are 100 %, which is not common in real applications, the limiting value of $P_k$ is 1.0 for all the nodes, at least in bounded networks. In many applications, the correct specification is to use realistic weighting factors and limiting probabilities when time t is approaching infinity.

In some applications the time horizon of the spreading process can be assessed and the corresponding value of time t in Equation (11) can be specified. When selecting the time value, the development phase of the spreading can be evaluated roughly as initial, mid-term, or long-term in scale of a time horizon. For these three time horizons and small networks, a convention like $t$=2, 5, and 8 may be used with Poisson distribution and $\lambda$=1.0. A small network is almost in its equilibrium state at time $t$=10. In larger networks the spreading is still going on in nodes far away from a source node or nodes. Depending on the application the unit of time $t$ may be 1 day, 1 month, 1 year, or something else.

## V. HOW TO SELECT THE MOST EFFECTIVE TEAM FROM A SOCIAL NETWORK

Because the team effectiveness is a combination of social and practical skills, the outcome of Equation (9) should be maximized. As discussed in the previous section, the functional form may not be as simple as in Equation (9) where the total effectiveness is a product of two terms. In this case, when individual practical skills of the team members or skills of sub-groups in the team are important, a more detailed expression, such as Equation (10) should be constructed.

An interesting consequence of different skill requirements may be that the optimal composition of the members may be composed of two or more weakly connected sub-groups in the network. These sub-groups are connected only by weaker ties than the ties inside each sub-group. Along these thoughts, our method provides tools to model networks of working groups in a social network. These groups may have different projects and corresponding skill requirements. Usually, these groups have also different activities, i.e. weighting factors, inside each group. In this paper, we consider only one group, possibly composed of several sub-groups. The problem is not always to select the members of a group; also existing configurations can be studied with the help of the methods of this paper. This problem, in fact, is easier and requires less computing power.

As modelling tasks and compositions of actors in a social network are highly specific to the problem at hand, we assume, in this section, that all the members of the team can execute the tasks of the project equally well. Secondly, this kind of modelling is a basic approach in the planning of a team composition and management of teams with commonly known methods. A novel contribution of this paper is to introduce the method to incorporate the effectiveness of social networking and social capital in the modelling and to describe how these two aspects, social and practical skills, can be combined and optimized.

In the model, the team from a social network is selected. Higher weighting factors are used inside the team and lower weighting factors are used outside the team. The interpretation of weighting factors describing activity is consistent with other quantities of the model. Activity is the probability of a node to receive social influence and intermediate the influence to its neighboring nodes in the network structure. The interaction between two nodes, when one node belongs to the team and the other one does not, obeys the same procedure. An essential feature of the model is that interactions between a team and the outside network structure can occur interactively several times from the team to the outside network, from the outside network to the team et cetera. Higher order interactions are weaker due to the weighting factors and time evolution of the spreading process.

The example network of Fig. 2 has fifteen nodes and nineteen bidirectional links between the nodes. The influence spreading process advances via the links between the nodes and the corresponding network topology. The model allows also unidirectional links and links with different strengths depending on the direction of a link. In a case, when this kind of empirical data is available, the model can be used as such. This is possible because all the nodes, links, and paths are modeled in a detailed level. For example, links are defined separately for both directions between two nodes.

Technically, the influence spreading has a source node (or nodes). Clearly, the source node must be a member of the team, and at the same time, this node represents a candidate for the manager of the group. The manager node, if a manager is appointed, provides the highest influence spreading in the network. As a primary method we take into account all the effects including both the influence inside the selected team and outside the team. The interactions between the team and the outside network members take place dynamically in the network structure all the time. This fact supports the choice of including also the effects of interactions between the team and the outside network.

The activity inside the team is higher compared to other interactions outside the team. The activity depends on the project and its tasks inside the team. In cases, where the project is difficult, social networking activities may be lower. The same team may have higher activity in a project when the members are more interested to contribute to the final outcome.

## VI. NUMERICAL RESULTS

The model is demonstrated by conducting numerical computations with the classic social network of Florentine family ties of 15th century [22]. The ties are marriages between the families. The method works for any social networks with bidirectional or unidirectional links between nodes. The method allows individual weighting factors for the nodes if this kind of information is available.

Fig. 3 shows the four most effective teams of three members, demonstrates the diversified temporal changes in team compositions in the network of Fig. 2. The most important variables are the activities of the team members and the activities of outsiders of the larger network. In the following, we denote $A=(a_t, a_n)$ where $a_t$ describes the activity value of team members and $a_n$ describes the activity value of nodes of the larger social network outside the team. Also, the size of a team has a great effect. Here, the teams consist of three members. In the calculations, the weighting factors describing activities are 0.5 and 0.1 for the team and outsiders correspondingly. These choices of weighting factors are believed to be typical for an active team and its social networks outside the team. Highly interactive nodes would have activities near 1.0. This kind of a situation may be rare in real-world teams of social networks and exists only in ultimate conditions, e.g. in the military, religious cults, or in terrorist organizations.

The team members and the most influential member are shown in Fig. 3 at time values $t$=1 and $t$=5. The results are for Poisson temporal spreading distribution with the strength parameter value of $\lambda$=1.0. The four most effective team compositions are shown for both moments of time. At time $t$=1 and $t$=5 the most effective team is {$\underline{1}$, 5, 9}. The nodes of the team, with the most influential node underlined, are listed in the parenthesis.

The upper part of Table 2 shows the numerical effectiveness measures of the most effective five teams at time $t$=1 and at time $t$=5 when effects in the larger network are considered. The managers are indicated by underlining. The lower part of Table 2 shows similar results when only the effects on the team members are summed in the effectiveness measure. In both cases, the interactions with the small team network and the rest of the larger network are taken into account. The only difference is that when calculating the value of the measure, the effects on the outside nodes are included in the sum in the first case, and are excluded in the second case. The differences of the corresponding values in the upper and in the lower part of the table provide a numerical measure for the effects on outside nodes $P_{Outsiders}$

$$P_{Larger\,network} = P_{Team} + P_{Outsiders}. \tag{12}$$

In the calculations, the source of influence is a node belonging to the team. During the influence spreading process all the nodes in the network interact with each other. Dotted lines in Fig. 4 show some examples of social interactions in the larger social network. Because loops are not considered in this paper, a node can exist only one time on a path. This limits the number of possible paths. In the method [28], loops can be calculated but some upper limit for path lengths are necessary to limit the computing time.

At time t=1 and at time t=5 the team of Nodes 1, 5, and 9 is the most effective, Node 1 being the most influential node (See Fig. 3 and the upper part of Table 2). Node 1 is a candidate for a team manager when social networking is preferred to technical skills as a favorable quality of the manager. The compositions of effective teams have changes from the initial phase ($t$=1) to the mid-term phase ($t$=5) when also other rankings are considered. At time $t$=1 the teams {$\underline{1}$, 3, 9} and {$\underline{1}$, 3, 5} are at the second and third places compared with {1, 5, $\underline{9}$} and {1, $\underline{5}$, 9} at time $t$=5. At time $t$=1 {1, 5, $\underline{9}$} and {1, $\underline{5}$, 9} are as low as 18th and 19th on the ranking list. Interestingly, the results on the lower part of Table 2 are different. Nodes 6, 7, 10, and 11 in different compositions form the most effective team of three members. Teams composed of Nodes 1, 5, and 9 have low rankings 7, 8, and 9 at time $t$=1 (and also at time $t$=5) with Nodes 9, 1, and 5 as the most influential nodes in this order (Table 2 shows only the first five rankings).

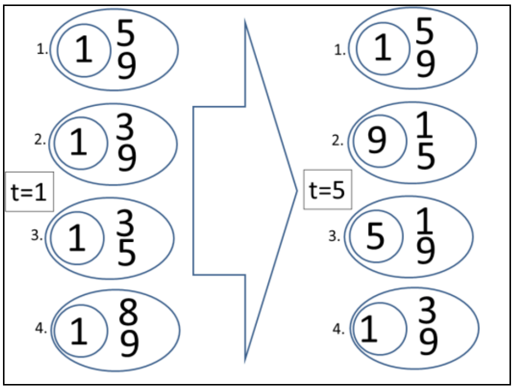


**Fig. 3.** The four most effective teams of three members of the network in Fig. 2 at time $t$=1 and $t$=5, $\lambda$=1.0. The team members are show and the most influential node is indicated in each team.

**Table 2.** Optimal composition of teams at times $t$=1.0 and $t$=5.0 are shown. The most influential team members are indicated by underlining. The upper part of the table shows the results of $P_{Larger}$ network and the lower part shows the results of $P_{Team}$ of Equation (12). The numerical values of the measures are also given.

| t=1.0 | Team | | | | t=5.0 | Team | | |
|---|---|---|---|---|---|---|---|---|
| **Larger Social Network** | | | | | | | | |
| 2.0196 | $\underline{1}$ | 5 | 9 | | 2.8553 | $\underline{1}$ | 5 | 9 |
| 1.9595 | $\underline{1}$ | 3 | 9 | | 2.7612 | 1 | 5 | $\underline{9}$ |
| 1.9579 | $\underline{1}$ | 3 | 5 | | 2.7605 | 1 | $\underline{5}$ | 9 |
| 1.9470 | $\underline{1}$ | 8 | 9 | | 2.6891 | $\underline{1}$ | 3 | 9 |
| 1.9469 | $\underline{1}$ | 5 | 8 | | 2.6781 | $\underline{1}$ | 3 | 5 |
| **Team Network** | | | | | | | | |
| 1.7322 | 6 | $\underline{7}$ | 11 | | 2.2617 | 6 | $\underline{7}$ | 11 |
| 1.7322 | $\underline{7}$ | 10 | 11 | | 2.2617 | $\underline{7}$ | 10 | 11 |
| 1.7322 | 6 | 7 | $\underline{11}$ | | 2.2616 | 6 | 7 | $\underline{11}$ |
| 1.7322 | 7 | 10 | $\underline{11}$ | | 2.2616 | 7 | 10 | $\underline{11}$ |
| 1.7249 | $\underline{6}$ | 7 | 11 | | 2.2491 | $\underline{6}$ | 7 | 11 |

Wealth of the 16 Florentine families have been documented. Node 1 (Medici) and Node 7 (Strozzi) have the highest wealth values of 103 (Medici) and 146 (Strozzi) of the families. Using the analysis, both families are discovered to be influential families when sub-structures of three nodes are investigated in the larger network of the 16 families. Medici is the leading family when the measure for the whole network is used and Strozzi when the sum is limited to the members of an inner circle of the team network. The latter can be regarded as a more egoistic way of thinking which can be appropriate when the ability to earn money is considered. This may reflect the different ways of building relations and co-operation of Medici and Strozzi families with other families.

Table 3 shows the most effective teams when 3–7 nodes are selected from the network of Fig. 2 (some results of three members are repeated). The results are consistent with the case of three team members. The numerical values of the effectiveness measure are presented in the second column ($P$). In the upper part of Table 3, all the effects of the larger network are taken into account as in Table 2. One node is added to the team when the number of members is increased. Node 1 (Medici) is the most influential node at time $t$=1, 5 for all sizes of teams between 3 and 7.

The effects on the team members are summed in the lower part of Table 3, excluding the effects on outsiders. At time $t$=1 the most influential node is Node 7 for 3, 4, and 5 members and Node 1 for 6 and 7 members. The composition of the team shifts from Node 7 (Strozzi) centric to Node 1 centric (Medici). At time $t$=1 for 5 members the composition {5, 6, $\underline{7}$, 10, 11} is the most effective team and for 6 members {$\underline{1}$, 3, 4, 5, 8, 9} is the most effective. These kinds of changes are results of the complex network topology.

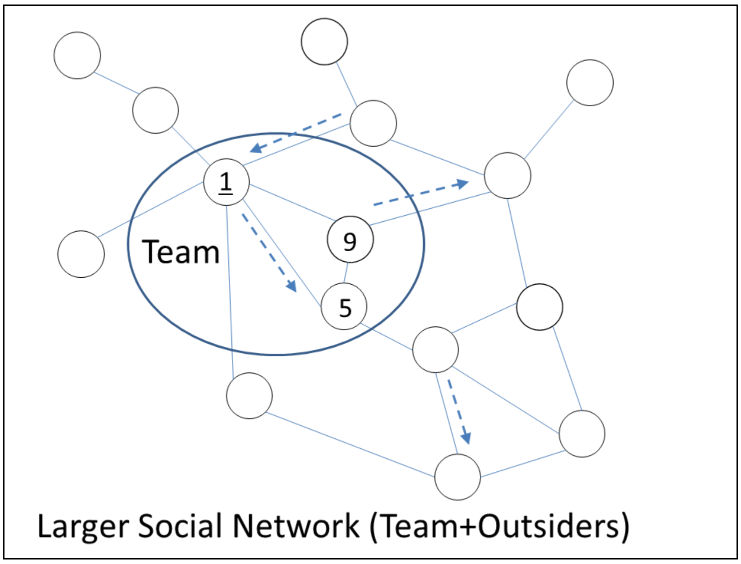


**Fig. 4.** Examples of possible interactions between nodes in the social network structure with one team.

**Table 3.** The optimal composition of 3–7 team members and the most influential nodes are shown for the two measures $P_{Larger}$ network and $P_{Team}$ of Equation (12) at time $t$=1 (left) and $t$=5 (right). The numerical values of the measures are also given.

| # Members | *P* | Larger Social Network (Team Members) | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 2.02 | 1 | 5 | 9 | | | | | 2.86 | 1 | 5 | 9 | | | | |
| 4 | 2.30 | 1 | 3 | 5 | 9 | | | | 3.36 | 1 | 3 | 5 | 9 | | | |
| 5 | 2.56 | 1 | 3 | 5 | 8 | 9 | | | 3.94 | 1 | 2 | 3 | 5 | 9 | | |
| 6 | 2.82 | 1 | 3 | 4 | 5 | 8 | 9 | | 4.39 | 1 | 2 | 3 | 5 | 8 | 9 | |
| 7 | 3.08 | 1 | 3 | 4 | 5 | 8 | 9 | 12 | 4.82 | 1 | 2 | 3 | 4 | 5 | 8 | 9 |
| # Members | *P* | Team Network (Members) | | | | | | | | | | | | | | |
| 3 | 1.73 | 6 | 7 | 11 | | | | | 2.26 | 6 | 7 | 11 | | | | |
| 4 | 2.14 | 6 | 7 | 10 | 11 | | | | 3.03 | 6 | 7 | 10 | 11 | | | |
| 5 | 2.45 | 5 | 6 | 7 | 10 | 11 | | | 3.53 | 5 | 6 | 7 | 10 | 11 | | |
| 6 | 2.67 | 1 | 3 | 4 | 5 | 8 | 9 | | 3.91 | 2 | 5 | 6 | 7 | 10 | 11 | |
| 7 | 2.99 | 1 | 3 | 4 | 5 | 8 | 9 | 12 | 4.40 | 1 | 5 | 6 | 7 | 8 | 10 | 11 |

In this paper, Poisson distribution is used as the model for influence spreading from a source node to its neighbours. In the model, all the different paths are computed and combined to give the overall influence of a source node. This is the ego centric approach. The method is not restricted to one source node: more than one parallel source nodes can be used. It depends on the problem which of these approaches describes the real-world situation better. In many cases, the ego centric approach is appropriate.

All the quantities are expressed as probability values which makes the method quantitative in all respects. No extra calibration is needed between the social networking part and the practical skills part when, in the first place, the importance of the social networking is taken into account at a correct level with respect to the practical skills.

The Florentine families' network is an example of a social network, albeit building teams may not be directly applicable. The results could be interpreted, in this case, as a possibility to form a smaller inside social network, a community of interest, with some common interests or business plans, as a part of the larger social networking structure of wealthy families in Florence. In fact, the empirical data describing the wealth of the 16 families is in excellent agreement with the theory of this paper. Social networking around families Medici and Strozzi are found to be the most effective. Medici is the most influential, when the effectiveness measure includes also all the effects outside the inner circle (team), and Strozzi is the most effective when only the effects on the selected members are summed. However, in the latter case, the benefits gained from the networking with the outside families are included in the sum.

## VII. Application To A Real-World Social Network Data

In this section, we demonstrate that the theory presented in previous sections can be applied to real-world social networks. The scalability of computations may be an issue with large social networks of more than one hundred nodes or hundreds of links between nodes. In this paper, we are studying applications where these computational limitations rarely come into being [25].

We are studying military task forces as a special case of the team member selection problem. There is no publicly available empirical data from military social networks. Owing to this fact, we use some other available network data that have similar, as close as possible, team and network structures of military operational groups and teams. The example network has been selected from several public databases having characteristics very similar to modern thinking in military contexts. The network has both work-related data and friendship data. Work-related data has both hierarchical and networked structures while friendship data is mostly non-hierarchical. Because partly the same structures exist in both networks, the network data are correlated. These characteristics are very similar, in our understanding, to the characteristics of military social networks. The data is not from a modern activity however this kind of data are almost timeless and may even suit us better because military organizations still often have traditional ways of acting.

We demonstrate the theory with a real-world social network of a tailor shop [26], (and Section VII in [28]). The social network has two kinds of data, instrumental (work- and assistance-related) and sociational (friendship, socioemotional). The example networks are shown in Fig. 5. The tailor shop has 39 workers: head tailor (Node 19), cutter (Node 16), and three lines of tailors (24 tailors), two button machiners, three ironers, and eight cotton boys. The instrumental network has 109 links between nodes and the sociational network has 316 links between nodes. The instrumental network is symmetric, meaning that when there is a link from Node X to Node Y, there is also a link from Node Y to Node X. The sociational network is asymmetric.

Table 4 shows results of the example social network for the two measures $P_{Team}$ and $P_{Larger}$ of Equation (12). We study the instrumental and sociational network data for different sizes (2–4 members) of small teams. The top ten optimal compositions are listed in the table. The most influential members, potential team leaders, are indicated and the numerical values of the two measures are also provided.

The measures are expressed as sums of probabilities which means that for the measure ($P_{Team}$) maximum value is always the number of team members. The model being quantitative, numerical values can be compared with each other in all dimensions. For example, higher values for sociational relations are a consequence of more friendship connections compared to work-related connections. Values for the larger network are higher because the effects on all nodes, also on nodes external to the team network, are summed. This means that in the military context, if a group is isolated during its operative action, the measure $P_{Team}$ may be more appropriate. On the other hand, if the team is working in continuous interaction with the larger network, $P_{Larger}$ better measures team performance.

In Table 4, we have used node weighting values 1.0 for relations between team members and 0.5 for relations between team members and members of the larger network. These describe more powerful interactions among the team members compared to interactions with the outside network. In the military context high values near 1.0 can be realistic but in other situations values 0.5, or less, may be appropriate. The strength of interactions depends on the situation and the actual operation, and eventually, is different for all the nodes in a social network. We have made some calculations with the lower weighting values of 0.5 and 0.1 and the results resemble the results for the values of 1.0 and 0.5. We conclude that the ratio of this two weighting factors is controlling optimal team structures more than their absolute values.

Next, we make conclusions about the results in Table 4. Nodes (members) 19 and 16 are the most prestige employees in the tailor shop. Node 19 is the head tailor and Node 16 is the cutter. In Kapferer's survey [26] the order of the three tailor lines are also evaluated. Interestingly, almost all the nodes in the optimal teams are composed of Nodes 19, 16, and line 1 tailors which, according to Kapferer's research, has the highest prestige among the tailors. Exceptions to this main rule in the larger social network calculations or in the friendship network are Nodes 32, 34, 37, and 31. They all are cotton boys on a low prestige level. These nodes don't show in the work- and assistance related network among the top ten list members (but all the eight cotton boys appear in the top 20 list except Node 35).

Now, we consider the work- and assistance related network in the view of the team measure $P_{Team}$. This may be the most important view because in this case the instrumental social network data includes both work- and assistance-level factors. Pure friendship data gives some extra information. In a military context the leading members Nodes 19 and 16 may not be suitable for an isolated operation outside the main organization. The model suggests several compositions of two member teams {3, 9}, {11, 12}, {9, 11},{3, 11}, and {3, 11} without Nodes 19 and 16. The difference between the two last teams is that Nodes 11 and 3 are the most influential nodes respectively. In an isolated network composed of only two nodes neither of the nodes is more influential than the other (assuming they have the same node weighting values), but in the model, interactions with the larger network have also some influence.

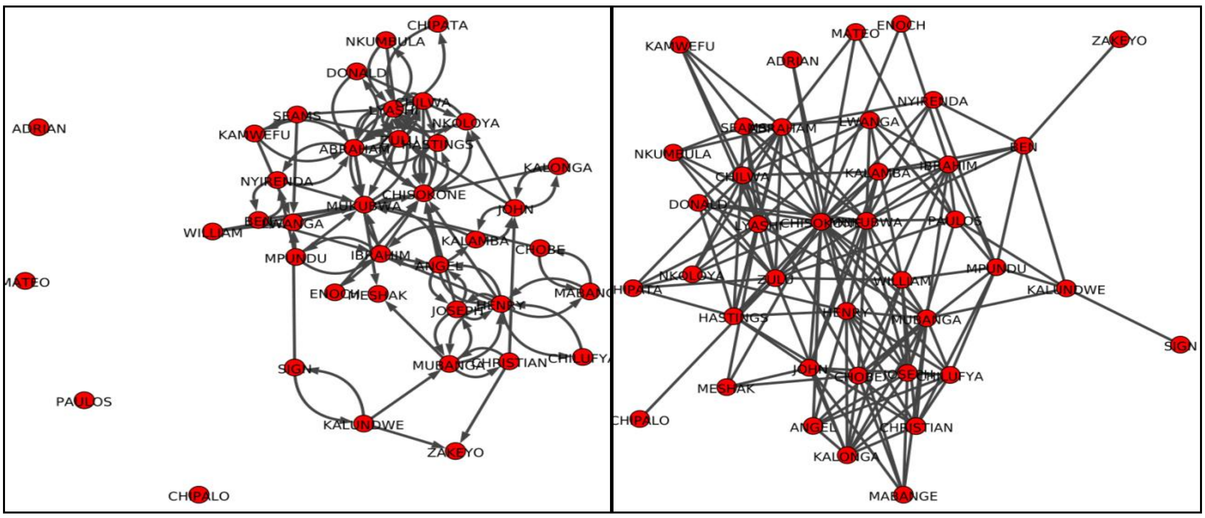


**Fig. 5.** Example social networks [26]. The left figure shows the instrumental (work- and assistance-related) and the right figure shows the sociational (friendship and socioemotional) network.

Further, three and four member teams {<u>3</u>, 9, 11}, {9, 11, <u>12</u>}, {3, 9, <u>11</u>}, {3, 9, 11, <u>12</u>}, and {3, 9, <u>11</u>, 12} have no Nodes 19 and 16 as their members in the top ten list. The measure containing larger network effects $P_{Larger}$ gives some different results. An interesting fact is that in the work- and assistance related network Node 19 is the most influential node in two, three, and four member teams except in the two member team {11, <u>16</u>}. In one team in the top ten list {<u>19</u>, 37} Node 37 is a cotton boy, more of them appearing in the top 20 list.

In the top ten list of the friendship network Node 16 is always a member of the team. Node 16 has more friendship connections than Node 19 and as a result Node 16 is often the most influential node. According to $P_{Team}$ measure, Nodes 19, 11, and 32 (a cotton boy) are the most influential nodes in some cases.

**Table 4.** Empirical instrumental (work- and assistance related) and sociational (friendships) data [26] from a tailor shop has been analysed. Optimal composition of team members and the most influential nodes are shown for the two measures $P_{Team}$ and $P_{Larger}$ of Equation (12). The most influential nodes are indicated with underlining. The numerical values of the measures are also provided.

| **Team Network, $P_{Team}$** | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Instrumental (work- and assistance-related) | | | | | | | | | | | | Sociational (friendship, socioemotional) | | | | | | |
| 2 members | | | 3 members | | | | 4 members | | | | | 2 members | | | 3 members | | | |
| <u>3</u> | 9 | 1.812 | 3 | 11 | <u>19</u> | 2.678 | 3 | 11 | 12 | <u>19</u> | 3.625 | <u>16</u> | 19 | 1.983 | 11 | <u>16</u> | 19 | 2.971 |
| <u>11</u> | 16 | 1.809 | <u>3</u> | 9 | 11 | 2.677 | 11 | 12 | 16 | <u>19</u> | 3.615 | 16 | <u>19</u> | 1.979 | 12 | <u>16</u> | 19 | 2.966 |
| 11 | <u>12</u> | 1.805 | 9 | 11 | <u>12</u> | 2.674 | 3 | 11 | 16 | <u>19</u> | 3.608 | 11 | <u>16</u> | 1.973 | <u>16</u> | 19 | 32 | 2.966 |
| 9 | <u>11</u> | 1.797 | 11 | 16 | <u>19</u> | 2.671 | 3 | 9 | 11 | <u>12</u> | 3.604 | <u>11</u> | 16 | 1.970 | 3 | <u>16</u> | 19 | 2.966 |
| 3 | <u>19</u> | 1.797 | 3 | 9 | <u>11</u> | 2.670 | 3 | 12 | 16 | <u>19</u> | 3.591 | 12 | <u>16</u> | 1.966 | <u>16</u> | 19 | 34 | 2.961 |
| 11 | <u>19</u> | 1.793 | <u>11</u> | 12 | 16 | 2.665 | <u>3</u> | 9 | 11 | 16 | 3.590 | <u>16</u> | 32 | 1.966 | 3 | 11 | <u>16</u> | 2.960 |
| 3 | <u>11</u> | 1.791 | 11 | 12 | <u>19</u> | 2.665 | 3 | <u>11</u> | 12 | 16 | 3.587 | 3 | <u>16</u> | 1.965 | 11 | 12 | <u>16</u> | 2.960 |
| 16 | <u>19</u> | 1.788 | 3 | 12 | <u>19</u> | 2.665 | 3 | 9 | <u>11</u> | 16 | 3.580 | 16 | <u>32</u> | 1.961 | 3 | 12 | <u>16</u> | 2.954 |
| <u>3</u> | 11 | 1.786 | <u>3</u> | 11 | 16 | 2.660 | <u>3</u> | 11 | 12 | 16 | 3.580 | <u>3</u> | 16 | 1.961 | 3 | <u>11</u> | 16 | 2.954 |
| 11 | <u>16</u> | 1.785 | 9 | <u>11</u> | 16 | 2.657 | 3 | 9 | <u>11</u> | 12 | 3.574 | <u>12</u> | 16 | 1.959 | 11 | 16 | <u>19</u> | 2.952 |

| **Larger Social Network, $P_{Larger\ Network}$** | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Instrumental (work- and assistance-related) | | | | | | | | | | | | Sociational (friendship, socioemotional) | | | | | | |
| 2 members | | | 3 members | | | | 4 members | | | | | 2 members | | | 3 members | | | |
| 16 | <u>19</u> | 10.159 | 11 | 16 | <u>19</u> | 11.229 | 3 | 11 | 16 | <u>19</u> | 12.253 | <u>16</u> | 19 | 24.098 | 11 | <u>16</u> | 19 | 25.186 |
| 11 | <u>19</u> | 9.769 | 3 | 16 | <u>19</u> | 11.182 | 11 | 12 | 16 | <u>19</u> | 12.220 | 11 | <u>16</u> | 23.859 | <u>16</u> | 19 | 34 | 25.177 |
| 3 | <u>19</u> | 9.757 | 12 | 16 | <u>19</u> | 11.177 | 3 | 12 | 16 | <u>19</u> | 12.199 | <u>16</u> | 34 | 23.838 | <u>16</u> | 19 | 32 | 25.155 |
| 12 | <u>19</u> | 9.715 | 14 | 16 | <u>19</u> | 10.829 | 11 | 14 | 16 | <u>19</u> | 11.887 | <u>16</u> | 32 | 23.810 | 12 | <u>16</u> | 19 | 25.116 |
| 14 | <u>19</u> | 9.391 | 3 | 11 | <u>19</u> | 10.803 | 11 | 16 | <u>19</u> | 24 | 11.845 | 12 | <u>16</u> | 23.785 | 3 | <u>16</u> | 19 | 25.056 |
| <u>19</u> | 24 | 9.365 | 16 | <u>19</u> | 24 | 10.779 | 3 | 14 | 16 | <u>19</u> | 11.840 | 3 | <u>16</u> | 23.718 | 11 | <u>16</u> | 34 | 24.999 |
| 15 | <u>19</u> | 9.257 | 3 | 12 | <u>19</u> | 10.744 | 12 | 14 | 16 | <u>19</u> | 11.835 | <u>16</u> | 24 | 23.634 | <u>16</u> | 19 | 24 | 24.960 |
| <u>19</u> | 37 | 9.242 | 11 | 12 | <u>19</u> | 10.740 | 3 | 16 | <u>19</u> | 24 | 11.797 | <u>16</u> | 31 | 23.520 | 11 | <u>16</u> | 32 | 24.912 |
| 11 | <u>16</u> | 9.207 | 15 | 16 | <u>19</u> | 10.659 | 12 | 16 | <u>19</u> | 24 | 11.791 | <u>16</u> | 30 | 23.492 | 11 | 12 | <u>16</u> | 24.872 |
| <u>19</u> | 33 | 9.138 | 16 | <u>19</u> | 37 | 10.643 | 3 | 11 | 12 | <u>19</u> | 11.765 | 13 | <u>16</u> | 23.460 | 12 | <u>16</u> | 34 | 24.866 |

## VIII. CONCLUSIONS

The team-building process is an important part of mission-centric planning and the presented method aims to support this approach by providing an effective pre-selection of potential teams. This paper proposes a method to select optimal candidates for team members. The generic analytical method was presented in Section III and an application for a real-world social network in Chapter VII. The reference networks and the results give promising results also from the end-user point of view.

The mathematical method is proposed for selecting the optimal team members from a social network. The method considers all the nodes in a social network, not just local nodes in a small part of the network. The method is based on probability theory where the influence of all the paths from a source node to a target node is computed with an exact closed form expression [27], [28], [25]. In case of a large social network or with limited computing resources, the path lengths can be limited. Usually, this provides a good approximation because in typical social networks the rule of six degrees [49] is valid. The rule states that average number of links between two arbitrary nodes in a large social network is five links apart from each other.

The total effectiveness of a team is composed of two kinds of factors: social networking and practical skills. We describe how these can be modelled and combined to get a measure for team effectiveness. In our numerical example, we assume that all the nodes in the team have equal practical skills. Taking into account the practical skills of individual members is possible, if they are known, because the model treats all the nodes of the network individually. We also describe how to model a project composed of tasks and sub-tasks in more complex cases.

Numerical results provide the composition of the best team members and, in the ego centric approach, the manager of the team. In addition, the algorithm provides also rankings and numerical effectiveness measures for all the possible combinations in a social network. Topology of the social network, size of the team, and activity values of team members and other network nodes are given as input values for the algorithm. Calculations are performed with exact closed form expressions. A novelty of the method is that all the paths in the influence network are computed using probability theory. This method considers with probabilistic terms possible common links at the beginning of different paths from a source node to a target node.

The methodology provides a tool to find the networked candidates and their potential to form the team. The team leader should approach the results critically and take into account the non-formalized issues, which might affect either the team itself or the surrounding organization. One example would be the negative effect of the assigned (and reserved) team members on the other teams or the general organization. We provide an example in the military context. Although a major officer might be analytically (and otherwise) recognized as a good team lead, it would not be beneficial to risk the functioning of the rest of the organization by assigning him/her as a team lead. Still, this is a matter for the Commander to decide.

The method of factoring the network and the candidates is a task in itself, and this paper does not cover the whole formalization process. It is enough to state, that the task is not easy, and it might be enough to formalize only the factors that are easy to formalize. The rest can be evaluated by normal experience- and education-based decision-making, and this approach enables the pre-selection process.

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