IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received June 30, 2021, accepted July 22, 2021, date of publication August 5, 2021, date of current version August 17, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3102850

The Impact of the Collective Members' Independence on the Prediction Accuracy

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ABSTRACT Decision making is one of the most frequently performed processes nowadays. Our future or other people's future may depend on the decision we make, therefore we try to take it as good as possible. The rapid development of technology facilitates it for us, as we are able to store, process and analyse more and more data. However, the power of human knowledge extended by experience and intuition still overperforms computer systems in solving such problems. The power of the combined knowledge of a group of people is known as a collective intelligence. In this paper, an analysis of one of the properties describing the consensus is presented, id est the influence between its members. The work is based on graph theory and a multi-agent system approach to formalise the problem. The new measures describing the collective and the accuracy of the final prediction were proposed. Experimental evaluations, based on the developed environment, followed by the statistical analysis of the obtained results allowed to observed four relationships between the considered measures describing the collective and the accuracy of collective prediction. The independence of the collective members plays a crucial role in the decision-making, therefore it should be carefully considered when selecting people for the collective, especially the large ones.

INDEX TERMS Collective intelligence, independence, knowledge management, multi-agent system, prediction.

I. INTRODUCTION

One of the most common processes performed nowadays by everyone is decision making. It regards every aspect of our life. The decisions may have a little importance, such as which movie should we watch in the evening or what should we eat for a dinner, as well as can be very essential and influence a lot on our future, a company or country future, etc. Therefore, it is important for us to consider all possibilities and predict the most probable and beneficial solution and based on that make the best decision.

The rapid development of technology facilitates decision-making processes. A huge amount of data is stored, processed, analysed and used by decision support systems to make our life easier. However, in spite of a wide range of different methods, algorithms and models there is still an extensive set of problems that cannot be solved automatically. Human's knowledge, experience, assumptions and instinct overperform computer systems in solving problems such as stock exchange trading, medical diagnosis, presidential election forecast.

Usually, during making a decision, people rely on the opinions of experts as they are authorities in a given domain. However, acquiring a group of experts could be a really difficult task because of costs and their accessibility. Luckily, it is not a great problem, since the collective intelligence has been discovered. A group of people, called a collective, that are not considered as experts, could make a more accurate decision than smaller groups of specialists [1].

A prediction problem, solved using collective intelligence, is presented in the Fig. 1 and could be described as follows. The whole process starts with a selection of the collective members. Then, each person tries to solve the problem on his own using his knowledge and assumptions. Such provided answers are collected and passed as an input to some integration algorithm, based on a Consensus Theory. As a result, we obtain a single collective prediction, that becomes the solution to the considered problem. After some time, when a real outcome of the event could be observed, the predicted value is compared with the real one and the accuracy, denoted

The associate editor coordinating the review of this manuscript and approving it for publication was Yichuan Jiang.

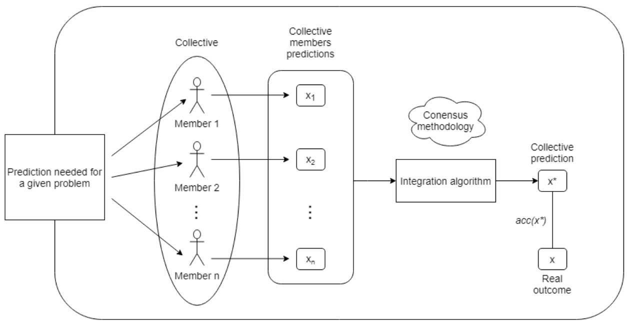


FIGURE 1. A collective prediction problem.

as *acc* in the Fig. 1 and defined formally in Section III-A, is computed. It describes how good the prediction was (how close to the real outcome), so the goal is to maximize this value.

The use of the collective intelligence in forecasting became the subject of sociological researches where authors wanted to find a relationship between the parameters describing a collective and the accuracy of their decisions. They have distinguished four main factors: collective cardinally, diversity, independence, decentralization and aggregation.

In this paper, we would like to focus on a property that has appeared least frequently in research, namely independence. It is defined as the strength of the relationship between the members of the collective and their impact on decision-making by a single individual. If the decision of one of the members is made separately from the others, without any relationships, the independence in such a situation is high, if it is based on the others opinions and knowledge, independence decreases. The high independence could be observed in a group of strangers, much lower in a team at work. Since its essence is not yet well known, therefore we have focused on the following goals:

- Introducing the representation of the collective in a formal way since in most similar studies it is not considered.
- Defining formally measures of the collective properties as well as the accuracy of prediction in comparison to the real outcome. Based on them, further statistical analysis could be conducted.
- Adapting a multi-agent system approach for collective prediction simulations and development of a dedicated environment as such a solution in the literature has been used just once, but in very basic form and with strict limitations.
- An experimental evaluation supported by statistical analysis that verifies whether the influence of the collective members' independence on the prediction accuracy is significant and how the combination of the independence, group size and members' relationship density affects the final outcome.

Determining the relationships between the aforementioned properties can be valuable, as based on them the first step of prediction solving, the selection of collective members can be significantly improved. It will bring many benefits in real-life applications, thus it is worth considering it in details.

The remaining sections of this paper are structured as follows. In the next part, an overview of related works is given. In Section III we briefly describe a collective prediction problem and multi-agent system, also we introduce the collective properties and measures that are used in this paper. Section IV is a main part of this article. It describes our approach and assumptions, experimental evaluation, achieved results and their statistical analysis. Section V gives brief summary and overviews our upcoming research plans.

II. RELATED WORKS

The prediction problem is well known in the literature. Even in the 80s of the previous century scientists become interested in an analysis of personal prediction. In [2] author verified the influence of historical, sociological, psychological, clinical and emotional impact on peoples and the quality of their decisions. As a result, the proposed 5 counsels how to make more conscious and vigilant decisions. Also in [3] author verifies and disproves the seven most deadly sins in this area, based on a trading and investment background. Presented analysis shows how to improve efficiency in financial strategy, marketing, and human resource management.

Such presented researches took into account only the prediction of a single individual. This approach is not sufficient in most cases, as the quality of the proposed predictions was not good enough. The presented analysis in [4], [5] shows, that formal and statistical methods overperform predictions made by a qualified specialist. Therefore, scientists began to focus on using the knowledge of a group of people, which was called a collective prediction phenomenon. It was proved that collective prediction superiors previously mentioned approaches. It really quickly become an applied tool in wide range of areas: economy [6], predictions of sport events results [7], [8] and political elections [9], [10].

In order to get more benefits from the collective intelligence, the authors began to analyze it very thoroughly to discover the most important properties influencing the accuracy of the prediction. In [11] author presented four main crowd characteristics that may impact its performance: cardinality - the size of a group of people, diversity - the variety of answers provided by participants related to the different state of knowledge they have and the diverse knowledge sources, independence - the strength of the relationship and their impact on decision-making, and decentralization - the ability of a member to specialise and rely on his own experience, assumptions and personal point of view. Initially, only sociologists conducted researches around these relationships, but this field quickly became the interest of mathematicians and computer scientists who wanted to formalize already described phenomenon.

The first two properties become the most popular in the researches. In [12]–[15] authors analysed how the size of the collective influences on the quality of the final result. All the studies consistently show, that better results were obtained with increasing the size of the population, however, from some extent, the results given by the collectives of subsequent sizes, did not differ statistically. This shows that the large size of a collective has a positive impact, as we avoid getting stuck in local extrema, but a too big number of experts is not necessary to solve the problem appropriately.

The second most frequently analyzed factor is diversity. The vast majority of researches show, that the diversity of the collective's members contributes to obtaining predictions with higher accuracy and better group performance [1], [16], [17]. In [18] author focused on the cognitive diversity of collective agents. His researches confirmed the previously stated thesis, that the higher diversity brings benefits, but also notices that it is applicable only for intermediate and complex tasks. However, not all the researches around diversity are consistent and lead to the same summaries. A bit different conclusion was drawn in [19]. Using a prediction market-based game as an experimental method they have proved, that indeed the higher diversity influences better performance, but after exceeding a threshold it starts decreasing and overall only the medium value of diversity has a positive impact. It shows, that it is vital to carry on researches in this area with deeper analysis, as there seem to be still a lot of undiscovered relations.

The independence factor is considered much less frequently. In [20] the authors conducted an experimental evaluation consisting of 5 phases in which 144 participants solved the estimation tasks. During the first stage, they estimated independently, in each of the next stages they were provided with answers given by the others. Results have shown that predictions made independently turned out to have the best accuracy, with each step their quality decreased. It indicates that increasing the influence between members of the collective negatively affects the final outcome.

Similar investigations to our could be found in [21], [22]. Based on the experimental evaluation and use of StockTwits data, they analysed the influence of participants independence, network decentralization and crowd size. However, in comparison to our studies, the authors focused only on the probability that the predicted value is right, not on the accuracy. Moreover, they did not take into account the structure of the collective and its connections density.

The collective intelligence is primarily related to people. However, the rapid development of technology, modern methods, algorithms and models allows us to replace real collective members with computer agents. More and more researchers [23], [24] adopt this approach in their investigations as it is cheaper and easier to manipulate during experimental evaluation preserving all the properties of the human collective. Especially the power of Artificial Intelligence, designed based on the human way of thinking, gives beneficial results. In the researches [25] the authors compared collectives consist of people, artificial agents and a hybrid one. The result showed that the accuracy of artificial intelligence predictions does not differ statistically from human decisions. In some plays AI agents gave worse decisions and the calibration of this approach was slightly lower, but after statistical analysis of all samples, the mean of the accuracy was statistically equal.

As a combination of computer systems and the features of collective intelligence, a multi-agent system has been introduced to researches for experimental purposes [26]–[28]. It faithfully mimics the structure of the collective and the single agent represents exactly the behaviour of a person. The systems introduced so far compose a good foundation, nevertheless, they do not take into account all the properties of the collective, for example, independence or density of connections, so it would be worth improving them for use in more detailed analysis.

As it could be observed, the described domain is popular in researches, however, some gaps still exist. Only a few researchers focused on the independence influence, however, they did not analyse the correlation between its value and outcome accuracy. Moreover, they did not take into account the structure of the collective (e.g. an average number of neighbours, a density of relationship), only the size was analysed. The aim of our researches is to verify the hypothesis stated by sociologists in a more formal way and to fulfill the uncovered areas.

III. COLLECTIVE PREDICTION PROBLEM

The collective prediction phenomenon is well known in the literature [20], [21], [29]. It uses the power of the collective (crowd), its diverse knowledge, experience and intuition in decision-making processes. It has been proved that a group of people, who are not experts in a given domain, often makes a better decision than a smaller group of experts [1]. Surowiecki [11] stated that a collective (crowd) is more intelligent than single individuals (from this collective). A crowd could be described using a set of properties and measures however that requires a more formal definition of the collective.

Definition 1: A collective could be represented as a directed weighted graph [30]. Let's define a graph: $G = (V, E, w)$ where V is set of vertexes representing collective members, E is a set of edges representing collective members' connections and satisfying $E \subseteq \{(v, u)|(v, u) \in V^2 \wedge v \neq u\}$ condition and $w : E \rightarrow [0, 1]$ is an edge weight function that represents the strength of members' relation.

Mentioned representation is presented in the Fig. 2. Members of the collective are presented as A1-A9, arrows represent the connection between members and w1-w11 their strength.

A. COLLECTIVE PROPERTIES AND MEASURES

A formally defined collective could be described using many different properties [11], [31]. This paper is devoted to independence analysis (influence of members' connections strength) therefore only some of them are taken into account.

A *vertex degree* represents the number of neighbours of vertex v (edges that starts in v).

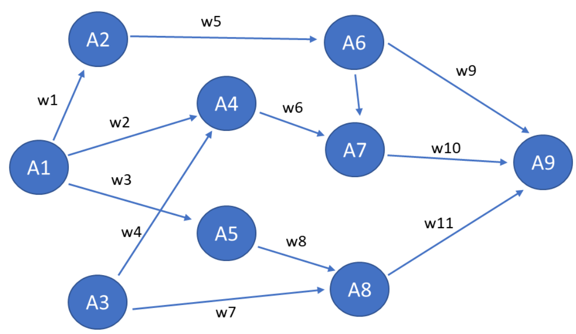


FIGURE 2. **A collective as a graph.**

Definition 2: A vertex degree denoted as $deg(v)$ is defined as follows:

$$
\begin{aligned}
deg(v) &= |N(v)| \\
N(v) &= \{u | v \in V \wedge u \in V \wedge (v, u) \in E\}. \qquad (1)
\end{aligned}
$$

Also, the properties of this measure could be defined:

- $min\ deg(v) = 0 \Leftrightarrow N(v) = \emptyset$,
- $max\ deg(v) = |V| - 1 \Leftrightarrow N(v) = V \setminus \{v\}$.

The mentioned measure identifies influencers, vertexes with high degree, that represent authorities, teachers, experts, people who are worth following. Mostly they reveal a high level of influence on their recipients. The maximum value of the vertex is assigned to the person who is respected by all members of the group. If someone does not have an audience his degree is minimum and equal to 0.

The vertex degree also allows us to define a measure that provides information about a graph density, number of connections between vertexes.

Definition 3: An average vertex degree of the graph G, that represents the density of it, denoted as $avg_{deg}(G)$ is defined as:

$$avg_{deg}(G) = \frac{1}{|V|} \sum_{v \in V} deg(v). \qquad (2)$$

Such introduced measure satisfies the following properties:

1) $min\ avg_{deg}(G) = 0$,
2) $min\ avg_{deg}(G) = \frac{|V|-1}{|V|}$ for consistent and acyclic graphs,
3) $max\ avg_{deg}(G) = |V| - 1$,
4) $G_1 = (V_1, E_1, w_1)$, $G_2 = (V_2, E_2, w_2)$: $avg_{deg}(G_1) \geqslant avg_{deg}(G_2) \Leftrightarrow \frac{|E_1|}{|V_1|} \geqslant \frac{|E_2|}{|V_2|}$.

Let us consider the properties in details.

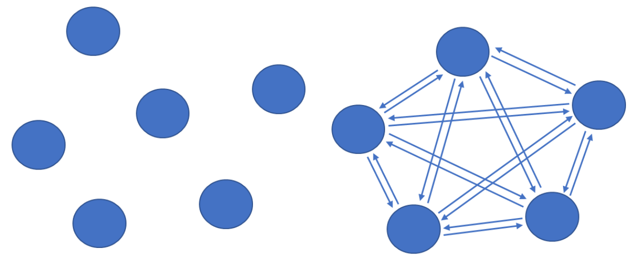
1) In general, when no additional assumptions are stated, the minimum value of an average vertex degree of graph G is 0. It could be noticed only if there is no edges in the graph.

Proof: Let $E = \emptyset$, then:

$$\forall_{v \in V}\ deg(v) = 0.$$

That implies that:

$$min\ avg_{deg}(G) = \frac{0 * |V|}{|V|} = 0.$$



(a) Graph without connections (b) A complete graph

FIGURE 3. **A graph with $min\ avg_{deg}(G)$ and $max\ avg_{deg}(G)$.**

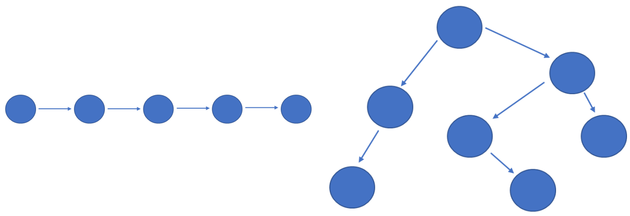


FIGURE 4. **A polytree.**

The analysed case, illustrated at the Fig. 3a, represents the situation in which all collective members are strangers, no one knows each other, so there are no connections between them.

2) In our researches, as we aim to verify the independence influence, we analyse consistent acyclic directed graphs to ensure, that collective members are connected (the influence between them exists). In that case the least dense graph is represented as a polytree (Fig. 4).

Proof: Let G be a polytree. From a definition we know, that:

$$|E| = |V| - 1.$$

We can notice as, that:

$$\bigcup_{v \in V} \{(v, u) | u \in N(v)\} = E,$$

which implies:

$$\sum_{v \in V} |N(v)| = |E| = |V| - 1.$$

Based on the above and Definition 1 we get:

$$avg_{deg}(G) = \frac{1}{|V|} \sum_{v \in V} deg(v) = \frac{|V - 1|}{|V|}.$$

A graph with the analysed structure can describe a group of people at the training, where everyone listens to the tutor, but the participants do not have mutual relations. However, in real life, such a collective is really rare.

3) A maximum average vertex degree occurs for a complete graph in which each pair of vertexes are connected with an edge (Fig. 3b).

Proof: A maximum average vertex degree of a graph requires that:

$$\underset{v \in V}{\forall} \; deg(v) = max\; deg(v).$$

From properties of the vertex degree measure (Definition 1) we know that:

$$max\; deg(v) = |V| - 1.$$

Therefore we get:

$$\begin{aligned} max\; avg_{deg}(G) &= \frac{1}{|V|} \sum_{v \in V} |V - 1| \\ &= \frac{|V| * (|V| - 1)}{|V|} = |V| - 1. \end{aligned} \tag{3}$$

A complete graph perfectly reflects the relationships in a group of friends or workmates, where everyone knows each other, cooperates, exchanges knowledge and opinions.

4) The last property is intuitive. The graph density depends on the ratio between the number of edges and vertexes. Among two graphs with the same number of vertexes, the denser is the one with the higher number of edges. Similarly, when the number of edges is equal, the graph with fewer vertexes is denser.

The next measure, required for conducted analysis, determines the influence between collective members. Firstly, the definition of *vertex average dependence* based on the strength of its connections is needed. As an inspiration of epidemiological systems, we have introduced the novel measure.

Definition 4: As a vertex average dependence, denoted as $d(v)$, we mean a measure:

$$\begin{aligned} d(v) &= \begin{cases} \dfrac{1}{|N'(v)|} \displaystyle\sum_{u \in N'(v)} w(u, v), & \text{if } |N'(v)| \geqslant 1 \\ 0, & \text{otherwise} \end{cases} \\ N'(v) &= \{u | v \in V \wedge u \in V \wedge (u, v) \in E\} \\ & w(u, v) - \text{an edge weight.} \end{aligned} \tag{4}$$

Thanks to this, it could be observed how the knowledge, conducted decisions, observations and cooperation with neighbours influence a prediction made by a single collective member. It allows verifying whether a single individual makes decisions on his own or is under pressure from the crowd. Also, it fulfills the following conditions:

1) $min\; d(v) = 0$,
2) $max\; d(v) = 1$.

The first condition occurs when a member is not under any influence.

Proof: Let us consider two case: when a vertex v does not have any influencers and second, when there are some edges ended in v.

1) The value of $d(v)$ in case of $|N'(v)| = 0$ is given in the definition and is equal to 0, so it satisfies the condition.
2) When $|N'(v)| \geqslant 1$ then:

$$d(v) = min\; d(v) \Leftrightarrow \underset{u \in N'(v)}{\forall} \; w(u, v) = min\; w(u, v).$$

From the definition of w we know that $min\, w(u, v) = 0$, so:

$$min\; d(v) = \frac{1}{|N'(v)|} \sum_{u \in N'(v)} 0 = \frac{|N'(v)| * 0}{|N'(v)|} = 0.$$

The minimum value characterizes influences who set trends up, scientists, explorers and who do not rely on the others opinions. Moreover, it describes the influence between people who hold opposite beliefs, even if the relationship exists between them.

A similar inference could be conducted for the maximum value.

Proof: Similarly as before, the maximum value of $d(v)$ could be reached only if:

$$\underset{u \in N'(v)}{\forall} \; w(u, v) = max\; w(u, v).$$

We know, that the value of $w(u, v) = 1$ could reach up to 1, therefore:

$$max\; d(v) = \frac{1}{|N'(v)|} \sum_{u \in N'(v)} 1 = \frac{|N'(v)| * 1}{|N'(v)|} = 1.$$

Such a value of $d(v)$ tells us, that a person v is totally dependent on int influencers. That case could be noticed when in a specific domain exists only a few sources of knowledge, consistent with each other, and the person follows all of them without self-reflection and opinion.

Based on the aforementioned vertex average dependence we proposed a measure representing an average dependence level of a whole graph.

Definition 5: An average dependence $avg_d(G)$ is represented in a following way:

$$avg_d(G) = \frac{1}{|V|} \sum_{v \in V} d(v). \tag{5}$$

Since it is a standard arithmetical mean of numbers from the range between 0 and 1 inclusively, therefore the minimum and maximum value of it is 0 and 1 respectively:

- $min\; avg_d(G) = 0$,
- $max\; avg_d(G) = 1$.

The higher the value, the stronger relationships exist in the collective. The value of the average dependence close to the maximum is typical for groups in which members collaborate a lot, exchange their insights and knowledge, follow the same principles and are usually at the same level of hierarchy. This could be seen within the teams at work. An opposite situation characterises groups where relations are weaker. A worldwide conference can be considered as an example. All members could be connected as they conduct researches in similar fields and read each other's articles, however, each of them may come from a different country, have a different background so the influences between them, apart from well-known and followed Professors, are much weaker.

Finally, for the evaluation of the obtained collective prediction, the accuracy measure is proposed and defined as follows:

Definition 6: Let x be an real event outcome value and $x*$ be a predicted value. As the accuracy of a prediction we call the following value:

$$acc(x*) = 1 - min(1, |\frac{x - x*}{x}|). \tag{6}$$

It allows us to verify how good the final prediction is in comparison to the real outcome. The distance function is commonly used for such purposes in the literature, therefore we adapted it also in this considerations. The normalisation of its values was used in order to simplify results comparison.

Same as previously, we can distinguish the following properties of the measure:

- $min\ acc(x*) = 0$,
- $max\ acc(x*) = 1$.

The minimum value, when the predicted value is opposite to the real one or even more distant, tells us, that the prediction is completely wrong. *Proof:* To minimise the value of $acc(x*)$ we have to maximise

$$min(1, |\frac{x - x*}{x}|).$$

Both of the arguments are non-negative, because of the absolute value of the second. Moreover, it could reach only up to 1, because of the first argument, so the maximum value of the statement is 1. Therefore:

$$min\ acc(x*) = 1 - 1 = 0.$$

Similar consideration was conducted for the maximum value.

Proof: In the analogical way, to maximise the value of $acc(x*)$ we have to minimise

$$min(1, |\frac{x - x*}{x}|).$$

To get the minimum value we need to focus on the second argument of *min* function. We know, that the value is non-negative, therefore the lower bound of possible values is 0 and is reached only if $x = x*$. Thus,

$$min\ acc(x*) = 1 - 0 = 1.$$

From the proof, we can notice that the maximum accuracy is reserved for the perfect prediction. Consequently, our goal is to achieve a prediction which value is as close as possible to the real outcome.

IV. EXPERIMENTAL ACCURACY ANALYSIS

The main part of our researches was devoted to an experimental analysis of the collective members' independence and its influence on the prediction accuracy using an aforementioned collective model, properties describing it and a specially designed simulation system. However, before we carried out the simulation, we had stated the hypothesis, that the high level of the collective members' independence positively affects the prediction accuracy and its value is especially important for a collective with a large number of connections between members (high collective cardinality or connections density).

A. SIMULATION SYSTEM DESIGN

Nowadays, acquiring people, especially experts, to solve problems, for example, prediction ones, is an expensive and time-consuming process. Engaging them for research purposes is really problematic as we would have to canvass a lot of them to verify many different sets of parameters describing them. To cope with that, for an experimental evaluation we can take the advantage of the power of technology development and use a computer system that imitates a real group of people preserving its structure, relationships, behaviours and other properties. In our analysis, we decided to use a *multi-agent system*.

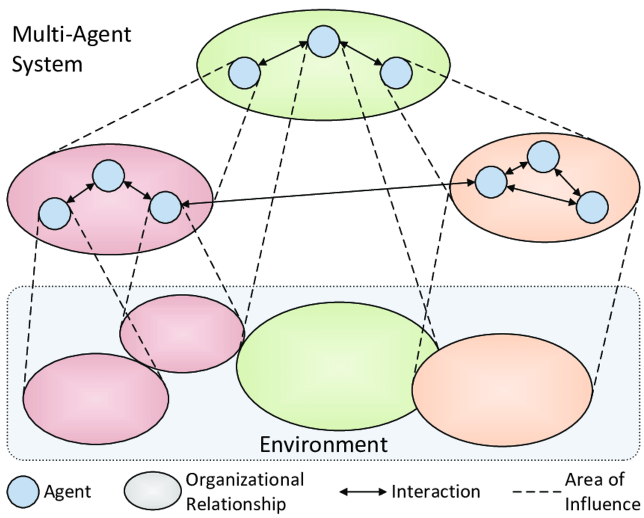


FIGURE 5. General overview of a multi-agent system [37].

Multi-agent system is a system composed of multiple computing elements, known as agents, which has two important capabilities. Each of them could solve the problem independently on its own, for example, make a decision. Moreover, agents can interact with the others exchanging the data, analysing others opinions or assumptions and so on [32]. A general overview of the system structure is presented in the Fig. 5. The behaviour of agents is similar to social activities. Therefore, such a designed system is used to solve problems that are difficult or impossible for a monolithic system to solve. In the literature, we can find many examples of its application in many various domains [33]–[36].

As an inspiration for our researches, we have found A-Trader system [27], [28]. It's a multi-agent system, that uses the power of the collective intelligence, dedicated to support decision-making in financial markets. Based on provided data agents predict stock exchange rates and decide whether it is worth buying, selling or leaving them as is.

However, the system is a significant simplification as the interactions between agents are not taken into account and have no impact on a single decision. Moreover, it analyses only 'current' values, does not support historical data. Also, it leaves out the strength of the relationships, therefore for our purpose, it is not sufficient as there is no opportunity to verify the dependency of the agents.

B. ENVIRONMENT

All the experiments were conducted using a specially implemented environment. The developed multi-agent system is extended in comparison to the previously presented A-Trader, in particular by the usage of historical data and the ability to define the strength of agents' relationships. There is a possibility to define different methods used by agents within the system. Each of them also has a specified set of knowledge sources from which it receives the data during the simulation. At the beginning of the single evaluation, each agent receives historical data to enable a learning phase for some of the algorithms. Then at each time tick, it receives actual values from its knowledge sources and influencers, base on which it makes a prediction and sends its answer to neighbours. All of them are collected and the final collective prediction is estimated. The achieved value is compared to the real one and the accuracy of a single decision is computed.

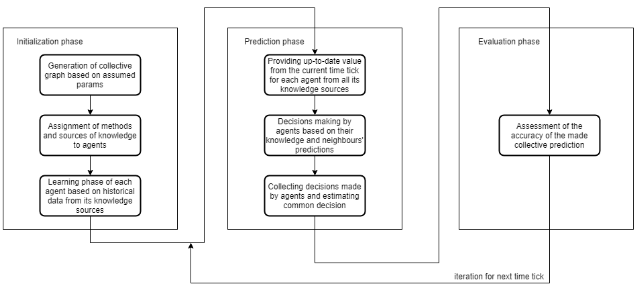


FIGURE 6. Overview of the simulation system.

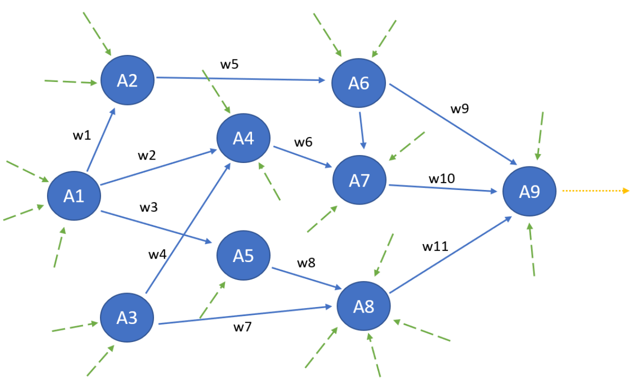


FIGURE 7. Simulation system data flow schema.

The schematic functional principle of the system is presented in the Fig. 6. Also, the Fig.7 shows an overview of a data flow in the system, where nodes of the graph, denoted as A, represent agents, blue arrows represent connections between them with a given influence rate w. Knowledge sources are marked with green dashed arrows. The final collective decision is presented using the yellow dotted arrow. As it could be seen, the multi-agent system schema and collective representation using a graph look exactly the same, therefore such kind of a system fits perfectly for a simulation purpose.

The simulation system allows defining the following properties of the evaluation:

- Collective size - number of used agents
- Prediction period - a period from which an agent takes data during a single prediction
- Set of training data - a historical data provided to an agent for learning purpose
- Time of prediction - for how far in the future the prediction is made (e.g. system tries to predict the value that will be in an hour or the next day)
- Inputs for agents - knowledge sources of agents
- Prediction methods - methods used by agents
- Average vertex degree - an average number of agent's neighbours
- Average dependence level - an average value of the influence between agents

In addition, we have equipped the system with the possibility of generating graphs using the aforementioned parameters. For generating vertex degrees we have used Gamma or Poisson distributions according to [38], [39] as they could be used to simulate a people connections graph (small-world networks). For a connections' weights generation, we have used Log-normal distribution.

The computational complexity of such a presented system is really difficult to estimate. Many of the aforementioned parameters strongly affect the time and efficiency of a single execution. One of the main aspects influencing this are methods chosen for agents. Agents could use simple methods such as calculating an average, however, they could also use very complex one, such as deep neural networks. The first set of algorithms does not require any training data, the second one needs it which also makes the whole process more complex and time-consuming. The more historical data is used and the more inputs are considered as knowledge sources for agents, the harder the execution is. Moreover, collective size also plays a crucial role in overall environment performance. Therefore, there is no possibility to compare the complexity of the developed system with other similar systems (for example with ATrader) since each of them has slightly different assumptions and in most cases, it is not possible to define different methods for agents (e.g. ATrader has a strictly hard-coded method for each agent, and the structure of the collective is predefined, not randomly chosen as in this environment).

C. EXPERIMENTAL EVALUATION

At the beginning of our researches, we have made some assumptions. Firstly, we have assumed that each agent will use exactly the same method, a neural network with the same structure, to reduce an undesired influence of decentralization. Additionally, we have provided each agent with exactly the same sources of knowledge, during an evaluation as well as a learning phase, to avoid the impact of diversity of collective members. As a source of data, we have used gold prices from Foreign Exchange Market. Parameters like prediction period, set of training data and time of prediction were fixed during testing of a single set of other parameters, however, they were changed between different executions to avoid overfitting with one specific set of data. We have used three different sizes of the collective: 5, 10 and 50. Very often for a jury, a committee or a group of judges 5 members are selected. The second group was selected twice as big as the first one, and normally it is difficult to select more experts due to their availability. The last group was chosen on the basis of other researches which show, that the greater size of the collective does not significantly affect the prediction accuracy. Next parameter, the average influence level $avg_d(G)$, was verified in the following variants: 0.3, 0.5 and 0.7. The boundary values such as 0 and 1 were omitted as this is not so common case in the real scenario, therefore some intermediate values were selected. The last but not least parameter, an average vertex degree of the collective $avg_{deg}(G)$, was set to 1 and 2 for the smallest collective, 2 and 5 for medium one and 2 and 10 for the largest consecutively. The smaller values were chosen to mimic a standard small-world network that often represents a group of people. It was also important to verify the constant value of $avg_{deg}(G)$ for each collective size to check how the number of connections (the more vertexes, the greater the number of edges) affects the final result. The second group of values represents collectives whose members are more likely to know each other. For each set of such defined parameters, the evaluation of the aforementioned method was repeated 100 times. All the achieved results were statistically analysed at the significance level $\alpha = 0.05$.

We have kicked off our analysis of the accuracy for the collective with a size of 5 and an average vertex degree equal to 1. At the beginning, we have verified if samples for different dependency levels come from the normal distribution. According to the Shapiro-Wilk test, we could not reject the null hypothesis stated that values come from a normal distribution for each of them as we have achieved $p-values$ greater than 0.05. Thus, for groups comparison, we have used a one-way ANOVA test for independent samples. According to $p - value = 0.017$ and $F = 4.34$ we have accepted the alternative hypothesis that samples do not come from the same distribution. Afterwards, we have compared an average for the samples in pairs. Conducted computations have shown, that the accuracy achieved at dependency level 0.3 is greater than accuracy at dependency level 0.5 by 0.27% and by 0.96% than at dependency level 0.7. The accuracy at the medium dependency level (0.5) is greater than achieved for the highest level (0.7) by 0.69%. It shows, that the higher level of dependency between collective members negatively affects the prediction accuracy.

Similar considerations were conducted for an average vertex degree equal to 2. Also in this case all samples come from the normal distribution according to the Shapiro-Wilk test. Same as previously, we have proved using the ANOVA test that samples do not come from the same distribution. Comparison in pairs has shown that the accuracy difference between the lowest dependency level and the medium is equal to 0.57% and 1.01% in comparison to the highest one. For dependency level 0.5 achieved results are better by 0.43% than for dependency level equal to 0.7. A conclusion is exactly the same as above, however, it could additionally be noticed, that the higher average vertex degree implies greater differences of accuracy between different dependency levels. The averages of achieved results for $avg_{deg}(G)$ equal to 1 and 2 are presented in the Fig. 8.

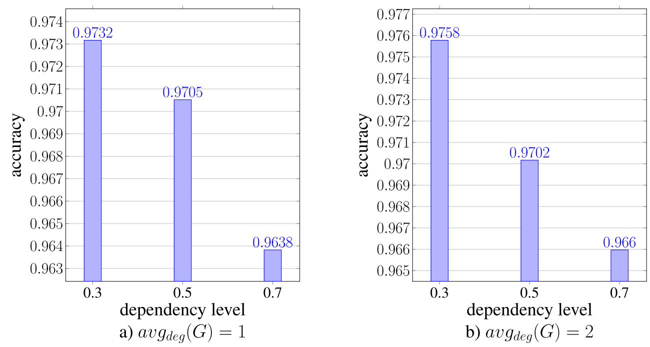


FIGURE 8. An average accuracy for collective size equal to 5.

In the next phase, we have focused on medium-sized collectives, where the size was equal to 10. Firstly, we have analysed low-density networks. According to the Shapiro-Wilk test, we could not reject the null hypothesis, therefore for further analysis, we have assumed, that all samples come from a normal distribution. A comparison using the ANOVA test has proved that at least one sample did not come from the same distribution as the others, as we have obtained $p - value = 0.039$ and $F = 3, 41$. Thus, we have compared samples in pairs. An accuracy achieved for the lowest dependency level was greater by 0.27% than for a medium level and by 1.13% in comparison to collective with the lowest independency. The accuracy for dependency level 0.5 is greater than achieved for 0.7 level by 0.87%. Taking into account also the previous considerations, we can draw another conclusion, that the bigger collective is, with a constant average vertex degree, the higher impact on prediction accuracy the dependency level exerts.

In the same way, we have considered an average vertex degree equal to 5 for medium-sized collectives. The verification of normal distribution of the samples has allowed us to use the ANOVA test for samples comparison and also in this case the alternative has been accepted due to achieved $p-value = 0.014$ and $F = 4.573$. As before, the accuracy for the lowest dependency level was the highest and was better by 0.92% than for the medium level and by 1.29% in comparison to the highest one. Collectives with a dependency level equal to 0.5 were able to make better predictions by 0.38% than their counterparts with higher dependency. Thanks to that we can realise, that for a collective with a low average vertex degree greater differences we can observe between higher values of dependency (between 0.5 and 0.7 difference is greater than between 0.3 and 0.5), for higher average vertex degree this relationship is exactly the opposite. The achieved results for medium-sized collectives are presented in the Fig. 9.

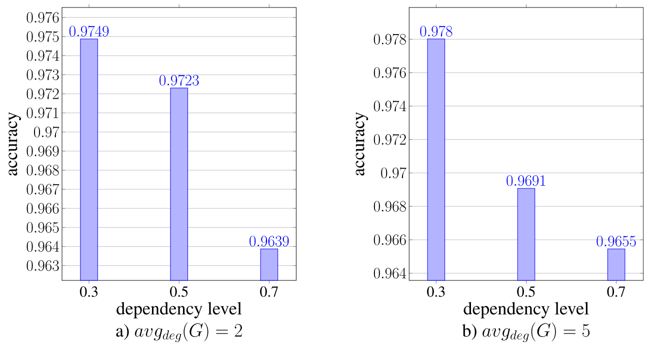


FIGURE 9. An average accuracy for collective size equal to 10.

The last part of our investigations was devoted to large collectives. Statistical analysis has been performed in the same way as for smaller networks. This time all samples also come from a normal distribution for $avg_{deg}(G)$ equal to 2 as well as 10. For both cases, the ANOVA test has rejected the null hypothesis that samples came from the same distribution. The comparison of the achieved accuracy in pairs has shown that its value for 0.3 dependency level was better by 0.39% and 1.23% compared to 0.5 dependency level and in comparison to the highest dependency by 1.24% and 1.45% for an average vertex degree equal to 2 and 10 consecutively. Collectives with medium dependency gave predictions better than with higher dependency one by 0.85% and 0.22% for $avg_{deg}(G) = 2$ and $avg_{deg}(G) = 10$. These results, presented in the Fig. 10, emphasise all four already drawn conclusions.

V. FUTURE WORKS AND SUMMARY

This article presents the experimental considerations about the influence of collective members independence on the final prediction accuracy. The mathematical representation of the collective as a graph allowed us to accurately evaluate this impact in isolation from diversity and decentralization, taking into account various factors describing the collective. The obtained results are a good indicator of selecting a group of people to solve the prediction problem.

Presented researches have shown, that the independence level significantly impacts the accuracy of the predictions. The higher the level is the more reliable prediction obtained. It's the most important especially for large groups of people between whom there is a high density of connections. The conducted researches have proved that an increase in both of mentioned factors negatively affects the forecast.

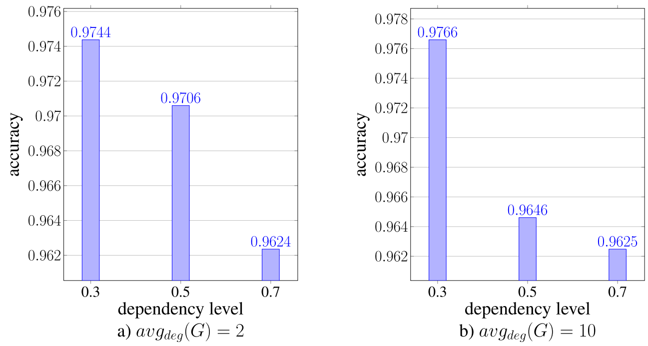


FIGURE 10. An average accuracy for collective size equal to 50.

Additionally, for such communities, a particularly large difference in quality can be observed when the influence level varies for relatively small values (from 0.3 to 0.5), whereas smaller differences are observed for higher levels of impact (from 0.5 to 0.7). For low-density collectives, this relationship is exactly the opposite. It suggests that for prediction tasks a relatively large collective with a low degree of influence should be chosen and, above all, with a low density of connections. As a conclusion, we should note that to solve prediction problems we should choose a relatively large collective with a small degree of influence between members and, above all, with a low density of connections.

The approach proposed in the article also has some disadvantages. The use of the multi-agent system, in which agents use a neural network as prediction methods, requires some historical data to perform the learning phase and then make reliable decisions. In the real world, people are able to make decisions based only on some assumptions without previous knowledge. Also, only one source of knowledge was used. For future considerations, it would be vital to extend it with wider background (for example economical considering gold price).

In the future, we would like to conduct similar investigations for decentralization and diversity comparison. As an extension to current researches, we intend to identify the synergistic influence of all known factors describing collectives on the prediction accuracy, taking into account also wider background and set on knowledge sources. We also plan to verify drawn conclusions using collectives consist of real people.

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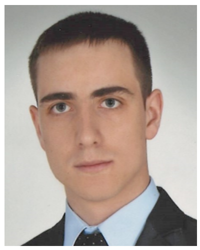

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