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Designing the Process of Random Selection of Citizens' Assemblies

Abstract: *The principle behind organizing citizens' assemblies is that their members are selected at random (Curato et al., 2021; Setälä and Smith, 2018; Warren and Pearse, 2008). Random selection is conducted in such a way that the composition of an assembly reflects selected demographic, social, or economic criteria in the same proportions as in the society as a whole (Fishkin, 2009). Inclusion of demographic criteria in the composition of the group creates a challenge with regards to how to draw assembly members in accordance with democratic principles (Flanigan et al., 2021; Smith, 2012). We propose that the priority for random selection should be given to accuracy in terms of how precisely the demographic criteria are reflected in the composition of the group. The method we have developed to achieve this is based on the algorithm of simulated annealing. Our findings demonstrate that simulated annealing yields positive results concerning the Closeness Index associated with accuracy. Additionally, this method creates a large number of unique panels, offering in this way a variety of possibilities for the volunteers to be selected to an assembly. A well-designed method for random selection improves the legitimacy of the citizens' assembly process, and thus of deliberative democracy.*

Keywords: deliberative democracy; citizens' assemblies; sortition; random selection; Accuracy Index; Closeness Index; simulated annealing.

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1. Introduction

A new form of democracy has taken root in recent years around the world — deliberative democracy (Bächtiger *et al.*, 2018; Dryzek, 2010; Fishkin, 2018). It is based on citizens' assemblies (deliberative mini-publics) that are composed of randomly selected and demographically representative groups of citizens, who come together to discuss and make informed decisions on public issues (OECD, 2020; Setälä and Smith, 2018; Curato *et al.*, 2021). Thanks to a carefully designed process of learning and deliberating that may take many meetings, citizens' assemblies allow the delivery of high-quality, well-thought-out decisions that contribute to the common good, thus presenting an opportunity for the revival and development of democracy (Dryzek *et al.*, 2019; Geissel, 2012; Smith, 2009).

Deliberative democracy has proven to enhance democratic legitimacy by fostering open and inclusive dialogue, which, combined with its focus on well-considered solutions, enables the formulation of thoughtful decisions (Curato *et al.*, 2017). It leads to policy acceptance and implementation by ensuring citizens' voices are heard and considered in the decision-making process (Curato, Hammond and Min, 2019). It allows citizens to overcome information asymmetry by providing access to expert insights, leading to evidence-based policymaking, while also mitigating polarization and building trust through civil and respectful dialogue among citizens with diverse viewpoints (Fishkin *et al.*, 2021). Furthermore, deliberative democracy promotes citizen empowerment and strengthens democratic citizenship by fostering meaningful engagement, collaboration, and ownership of public issues (Boulianne, 2019; Grönlund, Setälä and Herne, 2010). Citizens' assemblies that are a core process of deliberative democracy hold promise for addressing contemporary democratic challenges such as political apathy, disinformation, declining trust in institutions, and feelings of exclusion from decision-making (Gastil and Levine, 2005; Flanigan *et al.*, 2021; Newton and Geissel, 2012; Smith, 2012).

Random selection to political institutions was in use as early as in ancient Athens (Ober, 2008; Bouricius, 2013). In modern times, there have been several important improvements. Citizens' assemblies are based on the principle of equality, which means that potentially every citizen, regardless of their gender or financial status, may become a member of the assembly. However, the composition of the group is currently meant to reflect demographic, social, or economic categories as they exist in broader society. The aim is to create a mini-public or, in other words, a microcosm of society. In effect, the group is composed of ordinary people from different walks of life, who bring their personal life experiences and perspectives to discussions and final decision-making (Reuchamps, Vrydagh and Welp, 2023; Elstub and Escobar, 2019).

The categories used for the formation of a citizens' assembly may include gender, age, level of education, rural or urban area, region of the country, ethnicity, language, professional categories, and others. These categories are ideally selected in such a way that they create trust in the assembly among society. They are meant to ensure representativeness of the assembly. It is not representativeness in the statistical sense, as in opinion polling, because its size is usually not large enough. However, it does reflect certain features of society, which is meant to make it more trustworthy and reliable in comparison with a group created by pure random selection.

The process of recruitment to a citizens' assembly is conducted in two or three stages. Stage one usually comprises sending out letters with invitations to participate in the citizens' assembly to individuals or to households (this may also take the form of house-to-house visits or sending emails). Individuals or households are selected by lot using electronic means. Since registration is voluntary, citizens volunteer to participate in the assembly process by registering on a special website, by phone, or during a house-to-house visit. This creates a pool of volunteers. Once registration is complete, a second stage of random selection takes place. Its aim is to create a composition of the assembly that is demographically stratified. Since this stage involves electronic random selection, it is possible to draw, for example, 6 or 10,000 panels (compositions of the assembly), and as a next step, out of this set, select at random the final panel using a physical method, such as rolling a dice or selecting balls with numbers. This constitutes the third stage of the recruitment process.

2. Prioritizing Accuracy

The aim of organizing citizens' assemblies is to provide meaningful and effective solutions that will contribute to an improved quality of life for a given community. Therefore, how the process is designed and conducted is vital, as is who is in the decision-making group. Composition of the group in terms of its demographic features may have an influence on the outcome of the citizens' assembly. This is why we argue that accuracy in the random selection process — creating as representative a group as possible — is a top priority for the second stage of the recruitment process.

What does 'accuracy' mean in this context? Suppose that, in a given city, persons from the group 24–39 years old constitute 28 percent of the population. Then in the citizens' assembly of 50 members there will be exactly 14 seats allocated to persons from this age group. The same principle applies to all other categories, such as gender, level of education, ethnicity, etc. Random selection of 14 persons from the group aged 24–39 years, in this example, is considered accurate. Randomly selecting the exact number of assembly members for all demographic categories means achieving a perfect composition of the assembly.

In some cases, achieving a perfect composition of a citizens' assembly is not possible, due to, for instance, an insufficient number of volunteers with the desired demographic features. In order to measure the accuracy of random selection we propose two indexes: the Accuracy Index and the Closeness Index. Their use is presented in Table 1. In both examples, for the assembly of 50 members, there is a deviation by 4 seats (a difference between the desired value and the result). This is captured by the Accuracy Index which is a sum of all deviations by seat per subcategory. However, deviation by 4 seats may take place in different ways. In Example 1, there are 4 small deviations, and each of them is close to the ideal number of members for each age group. In Example 2, there is a significant deviation in the group aged 40–64 years. This is captured by the

Closeness Index, where the deviation by seat in each subcategory is raised to the power of 1.6 and then totalled (1.6 was selected because it provides a moderate increase of the index as the deviation increases for the subcategory).

Category	Subcategory	Desired values	Deviation — Example 1	Deviation — Example 2
Age	18–24	6	1	0
Age	25–39	14	1	4
Age	40–64	20	1	0
Age	65+	10	1	0
Accuracy Index			4	4
Closeness Index			4	9.19

Table 1. Two examples of deviation by the number of seats. 0 stands for perfect selection, 1 means there is 1 person more or less in the subcategory, and the same applies to other numbers. The lower the number, the more accurate is the selection.

In our view, the composition of the citizens' assembly is better, in terms of representativeness, in Example 1 than in Example 2. Therefore, the lower the value of the Closeness Index, the better.

3. Taking Equality into Account

The process of recruitment to the citizens' assembly should be based on democratic principles, and equality of all people is one of them. For this reason, every eligible citizen should have the chance of receiving a letter with an invitation to participate in the citizens' assembly — the initial pool of addressees should be as complete as possible, or in other words inclusive. During the first stage of recruitment, when letters are sent to individuals or households in all regions of the country or the city, care is taken to ensure that the number of letters sent to these regions is proportional to the numbers of their inhabitants so that everyone has an equal chance of receiving them (there may be, however, some exceptions to this rule).

Since it is the individual decision of people who respond to the invitation whether they would like to participate in the citizens' assembly or not, the result is a pool of volunteers with a mix of demographic profiles in a variety of proportions. This means that, in most cases, the chances for being selected are not equal to start with and, depending on who is in the pool of volunteers, it may not be possible to equalize it in any way.

For example, it may be that there is only 1 person in the pool with a primary level of education and there is 1 seat in the assembly for a person with this level of education. If the aim is accuracy of random selection, then his or her chances are 100 percent. At the same time there could be 200 people with a higher level of education in the pool, and in the assembly there would be 20 seats for this level of education. Their chances for being selected to the assembly are 10 percent, not taking into account other demographic criteria.

At the second stage of the recruitment process, ideally, all volunteers would have the potential of being selected to the assembly and their chances would be as close to equal as possible. However, if the aim is to achieve an accurate composition of the assembly, neither inclusiveness nor equality of chances may be possible in some cases due to the demographic profiles of the volunteers and the desired composition of the group. Inclusiveness and equality of chances can be improved by relaxing the desired demographic criteria and allowing stronger deviations from the ideal composition to occur. This, however, would have an impact on the representativeness of the assembly and its credibility. Therefore, in our view, it is the representativeness of the group that should be considered as primary in the process of random selection of a citizens' assembly. In order to ensure selection of an accurate composition of a citizens' assembly, we developed a method based on the algorithm of simulated annealing.

4. Employing Simulated Annealing

Simulated annealing is a probabilistic algorithm introduced by Kirkpatrick, Gelatt and Vecchi (1983) that makes it possible to find the global optimum of a given function. What the function describes here is an ideal composition of a citizens' assembly. The process starts with a high exploration phase which means looking for a solution across a vast range of options. A parameter called temperature is employed to determine this range. Then the exploration rate is gradually decreased, mimicking the process of cooling in annealing in metallurgy. In a physical annealing, a metal is heated above its recrystallization temperature and then it is allowed to cool down, changing its internal composition as a result.

Since its first introduction, simulated annealing has been further developed, and one of its versions is Generalized Simulated Annealing (GSA) proposed by Tsallis and Stariolo (1996). GSA turned out to be more efficient compared to the classical simulated annealing and fast simulated annealing, providing a fast convergence to the global optimum (Xiang *et al.*, 1997). It was implemented in the R package GenSA (Xiang, Gubian and Martin, 2017; Xiang *et al.*, 2013), and this is the version we have chosen for random selection of citizens' assemblies.

The key element for selecting citizens' assemblies using the GenSA package is the evaluation function, which is an instruction for the algorithm of what to search for. We have created the evaluation function in R in such a way that for each subcategory of the demographic criteria (e.g. 18–24 years in the age category), the value of the outcome of random selection is subtracted from the desired value and raised to the power of 2. The results of this operation for all subcategories are added and the overall result is the value of the evaluation function. If the composition of the assembly is perfect, the evaluation function equals 0. It is the use of this evaluation function that allows selection of panels with good results in terms of the Closeness Index, because, for each subcategory, the algorithm will search for the lowest value of the deviation.

The script for simulated annealing of citizens' assemblies may be used without prior knowledge of programming. Parameters for the draw are set in a regular Excel file, and the output of random selection is saved in Excel format as well. It is possible to give more weight to certain demographic categories (set priorities for them), if need be. The script is available for a free download from the website of the Center for Blue Democracy.[5]

5. Method

In order to analyse the performance of simulated annealing, research was conducted using 10 case studies from various countries. For each of these 10 case studies, drawing using simulated annealing was conducted 10,000 times. We have analysed both accuracy and equality related metrics. To analyse equality we have selected the Gini Index and standard deviation. Gini Index is commonly used as a measure of inequality among the values of a frequency distribution. A Gini Index of 0% indicates perfect equality, while a Gini Index of 100% indicates maximum inequality. Standard deviation is a measure that evaluates how dispersed the data is in relation to the mean. The lower the value of the standard deviation, the closer it is to the mean of the set. It is calculated for the frequency distribution, which relates to how many times each volunteer was selected to all panels.

Case study	Size of the assembly	Number of volunteers
Geneva	30	360
Two Regions	40	162
Lausanne	20	55
Rustavi	36	89
Kraków	60	564
Næstved	36	791
Greve	36	362
Copeland	30	96
Rzeszów	60	204
Miskolc	50	420

Table 2. Size of the assembly and the number of volunteers in all 10 case studies.

We have found that the value of the Gini Index improves for simulating annealing with subsequent draws until it reaches a plateau, which we call a ‘saturation point’, after which there is no significant improvement with subsequent draws. The saturation point may be reached after several thousand draws and is dependent on the data set. 10,000 draws were selected as sufficient for all of the cases. Simulated annealing was conducted mostly on a cluster that is part of the Topola cluster at the Interdisciplinary Centre for Mathematical and Computational Modelling at the University of Warsaw. A special version of the script in R was created for the use on clusters and supercomputers. It makes it possible to conduct a number of draws in parallel, and we used as many as 840 cores of the CPU at the same time.

As a point of reference for assessing the performance of simulating annealing, the leximin algorithm implemented in Panelot was chosen because of its common use. This method for random selection of citizens’ assemblies is available online at panelot.org. A challenge with regards to comparing simulated annealing with

5 Center for Blue Democracy, https://bluedemocracy.pl/random-selection/.

Panelot is that the desired set of categories is a basis for drawing using simulated annealing (it is specified in the input file), whereas Panelot allows the use of a perfect composition of the assembly as a starting point only if achieving it is possible. If this is not the case, Panelot provides a recommendation for 'a relatively easy way of making the quotas feasible' (Panelot, accessed in October 2023). What is meant here by 'quotas' is indicating a minimum and maximum range of deviation per seat that is allowed in a particular subcategory. For this reason, we have created two sets of input files for Panelot — one with the setting that was recommended by Panelot and a second one with the setting that was found by simulated annealing with a better Closeness Index than the recommended setting. The aim was to examine whether Panelot will be able to create panels with as good a Closeness Index as simulated annealing and, if so, then to evaluate other indicators related to equality of chances.

What is worth noting about Panelot is that it creates a set of 1 million panels each time. As a first step, it creates a set of unique panels, for example 100 or 500, depending on the data set, and then it duplicates them in such a way that probability for being selected is equalized for the volunteers that initially had low probability for selection. The panels are sorted into ranges and saved in the 'lottery.csv' file, which is available for the user for the final drawing. In order to analyse the performance of Panelot, we have created a script in R that calculates the values for indicators related to the accuracy and equality of chances, based upon the 'lottery.csv' file, the original set of categories and the pool of volunteers.

Accuracy was analysed using the Accuracy Index and the Closeness Index. These indexes were calculated as an average for each set of created panels per case study.

Inclusiveness of the methods was verified by checking whether each volunteer was selected to the panel in any of the draws conducted. In the case where every volunteer was selected to any panel at least once, inclusiveness was assumed to be 100%. Since the size of the pool and the size of the panel vary for each case, what is measured is relative inclusiveness, only for the particular number of draws.

Furthermore, we have calculated the number of unique panels for each set of draws conducted using simulated annealing and each set of panels generated by Panelot. A unique panel is a particular set of individual assembly members that is not repeated in other panels. The ability to generate them points to the creative potential of the method and it has an influence on the inclusiveness and equality of chances.

6. Results

The results of the study show that for 6 out of all 10 case studies, simulated annealing selected panels with a perfect composition in terms of demographic criteria, which is indicated by value of 0 for both Accuracy and Closeness Indexes. Panelot achieved Accuracy Index 0 in 5 cases. The best result for Panelot for the case of Lausanne was Accuracy Index 12, while simulated annealing found a perfect composition in this case. In 2 cases where a perfect composition was not found — Kraków and Rustavi — simulated annealing delivered better values of the Closeness Index than the setting recommended by Panelot. However, after adjusting the input files for Panelot with categories for the close setting created by simulated annealing, Panelot generated panels with values of the Closeness Index equal to those of simulated annealing. The difference is that, when using Panelot, one needs to know what the right setting is, whereas simulated annealing simply generates close results using the desired values for the subcategories.

	SIMULATED ANNEALING		PANELOT — recommended setting		PANELOT — close setting	
Case study	**Accuracy Index**	**Closeness Index**	**Accuracy Index**	**Closeness Index**	**Accuracy Index**	**Closeness Index**
Geneva	0	0	0	0	—	—
Two Regions	0	0	0	0	—	—
Lausanne	0	0	12	24.44	—	—
Rustavi	8	12.13	8	12.86	8	12.13
Kraków	12	18.63	12	23.20	12	18.63
Næstved	0	0	0	0	—	—
Greve	0	0	0	0	—	—
Copeland	10	14.13	10	14.13	—	—
Rzeszów	2	2	2	2	—	—
Miskolc	0	0	0	0	—	—

Table 3. Results for draws in relation to accuracy.

	SIMULATED ANNEALING				PANELOT				
Case study	**Inclusiveness**	**Gini Index**	**Standard deviation**	**Unique panels**	**Inclusiveness**	**Gini Index**	**Standard deviation**	**Unique panels**	Type of setting
Geneva	100%	23.86%	3.75%	10000	100%	19.88%	7.78%	342	
Two Regions	100%	26.87%	12.96%	10000	100%	26.72%	13.63%	97	
Lausanne	38.18%	63.55%	47.58%	2	49.09%	61.59%	43.25%	5	RS
Rustavi	55.06%	57.76%	44.14%	2960	55.06%	57.91%	44.57%	14	CS
Kraków	93.26%	64.24%	17.59%	10000	93.26%	60.53%	21.05%	475	CS
Næstved	100%	51.37%	5.06%	10000	100%	44.66%	6.90%	750	
Greve	100%	43.79%	10.73%	10000	100%	37.40%	14.44%	350	
Copeland	100%	47.53%	28.21%	10000	100%	46.33%	32.78%	74	RS
Rzeszów	93.63%	49.37%	27.94%	10000	93.63%	48.22%	30.45%	151	RS
Miskolc	100%	38.04%	9.04%	10000	100%	32.74%	15.31%	393	

Table 4. Results for draws in relation to inclusiveness, equality of chances, and the number of unique panels. 'RS' stands for setting for the categories that was recommended by Panelot, while 'CS' stands for the close setting created at random by simulated annealing.

When creating the graphs for frequency distribution, the number of draws was presented on the vertical axis as a percentage because, for simulated annealing, 10,000 draws were conducted, while for Panelot, the number of panels generated was 1 million. Thus, using percentages allows for an accurate comparison. Results were also normalized by converting them to percentage points when calculating the standard deviation.

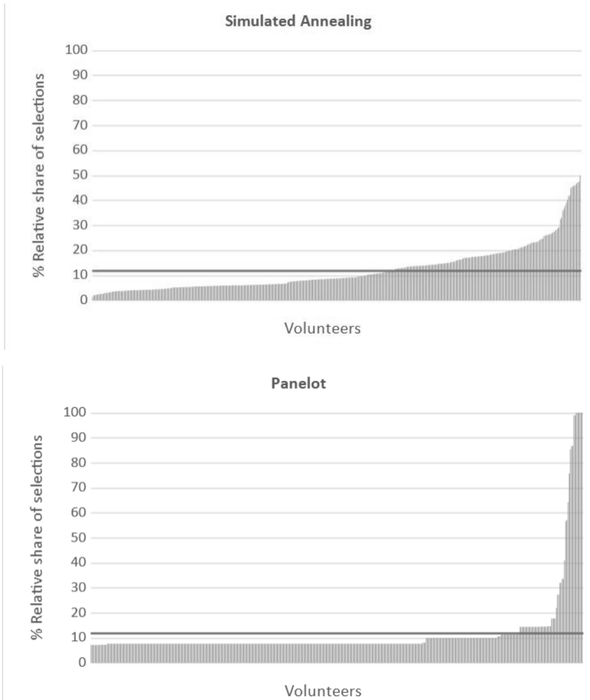

Figure 1. Number of selections per volunteer for the case of Miskolc (frequency distribution), arranged from the lowest number to the highest. Solid horizontal line shows perfect equality for all volunteers.[6]

Simulated annealing and Panelot provided the same levels of inclusiveness for volunteers for 9 out of 10 case studies. The difference was in the case from Lausanne, where the level of inclusiveness for simulated annealing was 38.18% and for Panelot 49.09%. The reason for this was that simulated annealing was set to find an Accuracy Index of 0 which resulted in finding just 2 panels with that composition of the assembly, thereby decreasing inclusiveness. For accuracy within a similar range to Panelot, simulated annealing allows for achieving higher inclusiveness and a significantly better result for the Gini Index (see Table 5 for details). In terms of the Gini Index for all case studies, Panelot showed better (lower) values, with a difference between 0.15% to 6.71% (an average of 3.46%).

6 Graphs for all 10 case studies are available for download from the Open Science Framework repository at: https://osf.io/nszft/

However, simulated annealing showed better (lower) values with regards to the standard deviation for 9 out of 10 cases. The exception was the case from Lausanne for the same reason mentioned above.

In 8 out of 10 case studies the number of unique panels selected by simulated annealing was 10,000 for 10,000 draws, while the highest number of unique panels created by Panelot out of all of the cases was 750.

Random selection method	Inclusiveness	Gini Index	Unique panels	Accuracy Index	Closeness Index
Simulated annealing	100.00%	48.46%	9986	10.57	10.85
Panelot	49.09%	61.59%	5	12	24.44

Table 5. Impact of the number of unique panels on inclusiveness. In the case of Lausanne, the function value for simulated annealing was set within a similar range as the best result generated by Panelot (for the recommended setting). The Accuracy Index for Panelot was 12, so the function value for simulated annealing was set at 13.8, which resulted in the average Accuracy Index of 10.57 (Accuracy Index ranging from 6 to 12, for 10,000 draws). The full capacity of simulated annealing for this case is an Accuracy Index 0, which means that if we set the function value to 0, the perfect composition of the assembly will be found. However, the number of unique panels is then just 2, and inclusiveness decreases to 38.18%, because the composition of only 2 panels meets the desired criteria.

The focus on accuracy when selecting a citizens' assembly is aimed at ensuring credibility of the group thanks to inclusion of the demographic criteria in exact proportions. The Accuracy and Closeness Indexes make it possible to evaluate how precise the composition of the assembly is, and they can be used to present to the public information about the accuracy of conducted draws. Simulated annealing, as a method for random selection of citizens' assemblies, is designed to achieve a high level of accuracy of draws, especially in terms of the Closeness Index. At the same time, it provides a satisfactory level of inclusiveness and equality of chances for volunteers. It is an easy-to-use method with a fully transparent code.

Data availability

The data sets analysed during the study are available in the Open Science Framework repository at: https://osf.io/nszft/.

Code availability

Scripts used for the study are available in the Open Science Framework repository at: https://osf.io/nszft/. Please note that the latest versions of the script for simulated annealing are posted on the website of the Center for Blue Democracy.

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Contributions

P.S. developed the core elements of the script for simulated annealing of citizens' assemblies, G.K. developed the scripts and conducted draws on a cluster, N.M. provided an overview of simulated annealing, P.P. conducted the literature review, A.M.G. created graphs presented in the text and supported data preparation, M.G. designed the study and led the writing of this article. The authors declare no competing interests.

Extended data

Graphs presenting the density function, Lorenz curve, and frequency distribution for all 10 case studies are available for download from the Open Science Framework repository at: https://osf.io/nszft/.

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