A Social Network Model for Integration of Refugees

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Abstract: The present work aims to study and model the integration of refugees who appear in a society, through the implementation of adaptive social networks. In our model, for each individual, their characteristics of religiousness and language skills are considered for the social integration. We also explore the homophily phenomenon as part of the creation of new connections and the changes on the refugees' traits. As it most commonly happens in real life, refugees appear in a community-structured social network as individual nodes without any connection, and interactions between refugees and non-refugees are built through a defined methodology which applies local search, random attachment and node deletion. We show a few case scenarios and perform a social network analysis.

1 INTRODUCTION

From July to September of 2016, 358.300 first time asylum seekers applied for international protection in the Member States of the European Union (EU), mostly Syrians, Afghans and Iraqis. It is undeniable that the arrival of refugees has impacted the lives of many countries in the past years, affecting many elections recently, especially in European countries, such as The Netherlands, France and recently the US, with the proposals of new policies to restrain the entrance of new refugees for the next future (Page, 2016).

As refugees become part of the life of cities around the world, it brings up an important issue: their integration in new societies and communities, especially in regard to the interaction with the locals. There is a wide range of studies that try to create some understanding about the processes of settlement of immigrants fleeing from their home countries (Ager and Strang, 2008; Korac, 2003; Krahn et al., 2012). Several approaches have been used in order to analyze the levels of integration between these two groups, through case scenarios from specific countries, different policies regarding immigration and residency allowance for refugees, etc. (Strang and Ager, 2010; Fasani et al., 2018).

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The discipline of psychology also has much to contribute to our understanding of immigrants and the process of immigration. Studies in acculturation and inter-group relations are focused mainly in two issues that face immigrants and the society of settlement: maintenance of group characteristics and contact between groups (W. Berry, 2001). Identity strategies employed by immigrants and their counterparts in the hosting country (especially attitudes toward immigrants and toward the resultant cultural diversity) can result either in a good integration or in marginalization and segregation of the new comers (Sheikh and Anderson, 2018; Puma et al., 2018).

In the context of analyzing social structures, network-oriented modeling can be considered as an alternative way to address complexity for modeling human and social processes, including the dynamics of the integration of new people in a pre-established group (or network) (Treur, 2016). In the present study, we present an analysis of an adaptive social network of nodes representing individuals in an environmental context. The interaction between people is translated through edges, and dynamic effects such as homophily are expected to affect the network evolution over time. As for the application domain, the aim is to understand, through the model, how the interaction between refugees and their local communities happens, knowing certain characteristics from the individuals which might affect these interactions. The present study applies, as far as known, the first

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methodology in literature directed to studying the integration of refugees in new communities through network-oriented modeling.

The following section presents the literature review which supports the decision to use religiosity (or religiousness) and language domain as the two main factors for our simulation. The literature also includes the social network modeling strategies applied in the simulations. Section 3 presents the temporal-causal model for the integration of refugees in a society in more details. Section 4 presents the results of the different simulations. Section 5 presents a technique of parameter tuning through simulated annealing to better fit the model to what we expected to obtain, and Section 6 includes some concluding comments and potential future works for improvement in our model.

2 SOCIAL NETWORK STRUCTURES AND THE INTEGRATION OF REFUGEES IN A NEW SOCIETY

In this section, we present the literature explored to build the model. We explain our choice for language skills and religiousness as factors that will define how connections are built, and also how the social network is generated based in a realistic approach.

2.1 Factors that Affect Refugees Integration

The problem of accommodation and integration of immigrants has been studied from many perspectives over the years. In the discussion on acculturation processes, there are three orientations, according to (Kuhlman, 1991):

> [...] those who want all immigrants to adopt the dominant majority culture, the advocates of a 'melting-pot' (i.e. the blending of cultures and races to produce a new national culture), and those who favor ethnic pluralism in which communities retain much of their original culture and the country becomes a federation of nationalities.

(Kuhlman, 1991) studied Eritrean refugees in the region of Kassala (Sudan) and created a framework to explain the issue of involuntary immigration in developing countries from an economic perspective. Their proposed framework has four independent variables with characteristics of the refugees themselves, factors related to the process of flight, characteristics of the region of settlement, and policies related to refugees. The dependent variable is the integration. From the characteristics of the refugee are included (1) demographic variables, (2) socio-economical background and (3) ethno-cultural affiliation.

From the demographic characteristics of refugees, are listed criteria as age, sex and household composition. From socio-economical background are included educational level, occupation before immigration and a distinction between rural and urban refugees. For ethno-cultural affiliation of refugees, are included factors as as native tongue, religion and place of birth.

(Krahn et al., 2012) shows the impact on labour market for refugees from Yugoslav and Russia in the 90s, and points out that *the level of English language training they received was inadequate to meet the requirements of their occupations*, when comparing immigrants with Canadian-born workers with the same level of education and professional degree. In the work done by (Ager and Strang, 2008), elements central to perceptions of what constitutes 'successful' integration in the UK are identified. The framework contains four main domains of integration, (1) foundation (right and citizenship), (2) facilitators (language, cultural knowledge, safety and stability), (3) social connection (social bridges, bonds and links) and (4) markers and means (employment, housing, education and health). Regarding the social connections, (Ager and Strang, 2008) shows that both immigrants and people within the community had expectations of a community where there was active 'mixing' of people from different groups, with 'belonging' being one of the marks that would identify a successful integration.

Apart from the view of the need for integration, it is shown in many studies that the maintenance of tradition brings many benefits to the refugees, like health and the integration itself (Beiser et al., 1993). The frequency and quality of contact between refugees and non-refugees is also an important aspect that helps integration. (Ager and Strang, 2008) states that:

> In the course of our fieldwork, both refugees and non-refugees suggested that an important factor in making them feel 'at home' in an area was the friendliness of the people they encountered on a daily basis. [...] Conversely, perceived unfriendliness undermined other successful aspects of integration.

The language is also considered as central for the integration process by (Ager and Strang, 2008), affecting the social interaction, economic integration and full participation in society. Researchers were able to conduct longitudinal analysis and learned that language skills are needed for meaningful contact rather than vice versa (Collyer et al., 2017). Along with the language, refugees' knowledge of national and local procedures, customs and facilities and, though to a lesser extent, non-refugees' knowledge of the circumstances and culture of refugees are also relevant.

Religiousness is here expressed by how religious an individual is, regardless of the religion branch. A correlation between depression and religious practice in Lebanon's elderly is found by (Chaaya et al., 2007). The sample taken from a refugee camp that had no access to the mosque showed a higher level of depression, due to lack of socialization. It is also shown that minority groups rely on religious stratagems to cope with their distress more than other groups do (Dunn and Horgas, 2004).

As discussed above, in many works within psychology and sociology of refugees, the complexity of the phenomenon of integration and/or acculturation is big. Tackling all the aspects demands a complexity that does not guarantee a total accuracy in respect to reality. Nevertheless, some factors are present in many works and can be addressed for a simplified, yet also relevant perspective over the problem. For this work, we chose religiousness and language skills as the factors that will define integration and construction of new bonds between refugees and non-refugees.

2.2 Building a Social Network of Community and Refugees

Network-oriented modeling is an approach that combines social network analysis in the search of understanding phenomena that can be represented as networks (Treur, 2016). These applications are seen in many fields of study, but recently much is found in the study of social relations. As one can use nodes and edges to represent objects and relations, this approach is appropriately suitable for our objectives.

(A. Beaman, 2012) uses social network analysis to evaluate how the construction of a social network influences the success of refugees in the US labor market. The results indicate that an increase in the number of social network members resettled either in the same year or one year prior to a new arrival leads to a deterioration of outcomes, while a greater number of tenured network members improves the probability of employment and raises the hourly wage.

Both studies by (Beiser et al., 1993) and (Beiser and Hou, 2001) demonstrate how language skills, combined with employment, can be used for prediction of depression in Asian refugees. (Chaaya et al., 2007) also shows how religiosity can be influencing depression in older people in Lebanese refugee camps.

Moreover, many works aim to gather longitudinal and ego-centered data about refugees and build social networks for analysis (A. Beaman, 2012; Koser, 1997; Ryan et al., 2008; Williams, 2006). However, no work addressing simulations and predictions of future situations of refugees regarding their integration using the traits of people in a social network were found.

So as to mimic a real network with the properties chosen for the model, it is necessary to build a social network which can handle weighted edges, and where homophily can be incorporated to handle the changes in the node states. The work done by (Toivonen et al., 2007) is a very suitable and good inspiration for our work. They present a model which simulates real networks taking into account the theory of weight-topology correlations as their basis. The model will be better explained in the next Section.

3 CREATING A COMMUNITY AND MANAGING THE TIES

This section explains how the network which represents the population of a society is created. In order to do so, we explain the model created by (Toivonen et al., 2007), as well as the adaptations that were made in order to adequate the model to our purposes.

3.1 A Model for the Creation of a Community of People

Social networks are a very suitable approach to represent a community, where the nodes represent the individuals of a society and the connections represent the bonding between these individuals. As human relations change over time, some phenomena might be implemented, such as nodes dying or leaving the community, connections being strengthened or weakened, new nodes becoming part of the network, etc.

The algorithm proposed by (Toivonen et al., 2007) works over a fixed size of network defined as N nodes, initially not connected with each other and with no state values. Afterwards, the algorithm operates over them by creating and modifying their relations based on random attachment, local search and node deletion, providing a stabilized network as an output. We consider a network to be stabilized when it follows the community structure of a social network with strong

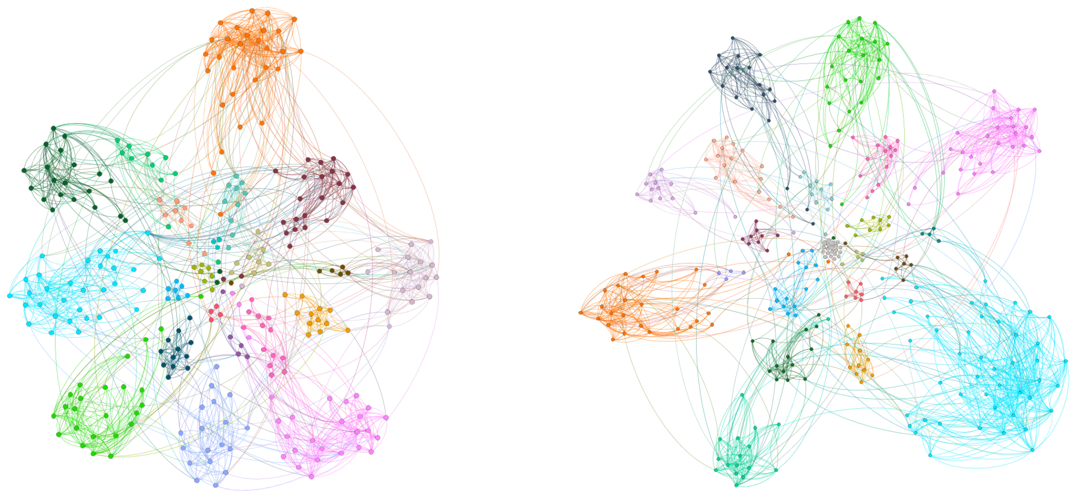

Figure 1: A social network with 300 nodes and a community structure (left). Each community is represented by a different color. Next, there is an insertion of 20 isolated nodes without any connections (right), representing the refugees (in gray).

connections inside the communities and weaker ones connecting the communities (S. Granovetter, 1983).

The local search mechanism is a two-step procedure in which every node has the chance to choose a neighbor and increment the connection between them (first step). Then, it proceeds by choosing one of the neighbors of the first chosen node, enabling their connection to be strengthened (second step). In the second step, if the node and the neighbor of its chosen neighbor are already connected, then their connection is strengthened by an increment value. If they are not connected, then they have a chance to connect with each other. This corresponds to the real-life situation in which if a person has strong ties with two others, then these latter two have a high chance to get connected. This is also known as the weak tie hypothesis, introduced by (Rapoport, 1957).

The random connections that we can create in real life are represented through the random attachment mechanism. In the algorithm proposed by (Toivonen et al., 2007), if a node is not connected with any other node after one step of finding new friends at random, then it gets connected to a random one.

The last procedure is the node deletion, through which a node has a slight chance to be deleted in every step. If a node gets deleted, then its connections are deleted as well. The deletion of nodes can be interpreted as a mechanism of preventing the network from becoming a clique, whilst it also represents, for the dynamic network, link removals between nodes, thus a sudden breakdown of the relationship between two nodes, as in real life relationships can end. In order to prevent the elimination of the network, if a node is deleted then a new one appears in the next time step.

Some described parameters were considered necessary and are listed as follows (Toivonen et al., 2007):

- p_r : probability of a node to establish a new link with another randomly chosen node (used in random attachment);
- p_Δ : probability of two nodes connected to the same node, to be connected (used in local search);
- p_d : probability of a node to be deleted (used in node deletion);
- δ : weight increment;
- ω_0 : initial weight of a new connection.

For our simulations, we kept the original probability values provided by (Toivonen et al., 2007), $p_r = 0.0005$, $p_\Delta = 0.05$ and $p_d = 0.001$. The values for the weight of the edges have been normalized between the range of $[0,1]$. Therefore, we have decided to keep low values for δ and ω_0, with values of 0.0001 and 0.0001, respectively. These value choices are small enough so that the weights of the edges do not exceed 1 rapidly throughout the simulation lifetime. Nonetheless, these values can be adjusted in order to represent reality as accurately as possible. If people tend to increase their bonding faster, then δ should be higher, otherwise it should be lower. Also, ω_0 can variate depending on the initial bonding level connecting people. For the purposes of the current case of study, it was decided to keep these values static as 10^{-4}.

The algorithm runs these three procedures for N nodes and for a specific number of steps. Figure 1 on the left illustrates the output graph for a simulation after running it for 25.000 steps upon $N = 300$

Table 1: Traits of the populations inside the community. Random values are uniformly distributed within the ranges.

Community	Lang. skills	Religiousness
Refugees	$[0.0, 0.2]$	$[0.7, 1.0]$
Local population	$[0.6, 1.0]$	$[0.0, 0.4]$

nodes. The network has a community structure and each community is shown in a different color. The total number of communities in this example is 21. Results showed that strong connections are occurring between nodes in the same communities and weaker links connect the communities. On the right side, it shows the same social network of 300 nodes after the insertion of 20 isolated nodes representing the new refugees recently arrived in this particular society. From this status, we included our mechanisms to cope with the homophily effects in the relationships within the community.

3.2 Incorporating Traits of Language Skills and Religiousness

After the initial community is established, the language skills and religiousness values in the nodes are set, representing local population and refugees according to Table 1, at random. As expected, the language skills of the local population is higher than the recently arrived refugees. Moreover, the religiousness of each node from the local population is also much smaller than the refugees population, simulating the context of a secularized society receiving immigrants from religious areas.

After attributing values for these two traits to all the nodes in the population, we incorporate the effects of homophily and social contagion in each node over time. The mechanisms of random attachment, local search and node deletion are still running, but now the state of the nodes is affected by their relationships.

3.3 Numerical Representation of the Homophily Principle for the Weight of the Edges

The values for the weights of the edges are updated over time using homophily, which indicates that the more similar the states of two connected nodes are, the stronger their connection will become (Treur, 2016). Node values alone are not representative of the homophily effect, but their absolute differences are. The values of two connected nodes can be here generalized as X_A and X_B. Furthermore, a threshold value $\tau_{A,B}$ is understood as being the reference value above/under which the absolute differences of node values should be so that upward or downward weight changes occur, respectively. These thresholds are present in Equation 3 when calculating the changes in the connection weights and have a fixed value of 0.1. Their role is explained as follows:

- an **upward change** of the connection weight $\omega_{A,B}$ occurs when $|X_A - X_B| < \tau_{A,B}$
- **no change** of the connection weight $\omega_{A,B}$ occurs when $|X_A - X_B| = \tau_{A,B}$
- a **downward change** of the connection weight $\omega_{A,B}$ occurs when $|X_A - X_B| > \tau_{A,B}$

The update of the the edge weights is calculated through Equation 1, given the actual weight of the connection between two nodes A and B at a time-step t, $\omega_{A,B}(t)$, a speed-factor $\eta_{A,B}$, and a function $c_{A,B}$ representing the combination of the aggregated impact caused by B in A.

$$\omega_{A,B}(t+\Delta t) = \omega_{A,B}(t) + \eta_{A,B}[c_{A,B}(X_A(t), X_B(t), \omega_{A,B}) - \omega_{A,B}(t)]\Delta t \quad (1)$$

The advanced quadratic function based on (Sharpanskykh and Treur, 2014) was chosen to update the edge weights, as shown in Equations 2 and 3. X_A and X_B are the states of person A and person B, respectively, $D = |X_A(t) - X_B(t)|$ is the difference between the two node states, $\eta_{A,B}$ is the update speed parameter for the connection from person A to person B, and $\tau_{A,B}$ is the threshold for connection adaptation.

$$c_{A,B}(X_A, X_B, \omega_{A,B}) = h_{A,B}(D, \omega_{A,B}) \quad (2)$$

$$h_{A,B}(D, W) = W + Pos[\eta_{A,B}(\tau_{A,B}^2 - D^2)](1-W) - Pos[-\eta_{A,B}(\tau_{A,B}^2 - D^2)]W \quad (3)$$

In Equation 3, $Pos(x) = (|x| + x)/2$, which returns x when $x > 0$ and 0 otherwise.

3.4 Numerical Representation of the Social Contagion for the State of the Nodes

In parallel to the weight evolution, the node values for the states are also changing. The effects of social contagion are expressed in the evolution of node values. The modeling of such phenomenon is given through the differential Equation 4:

$$X_B(t+\Delta t) = X_B(t) + \eta_B[c_B(X_{A1}(t), \ldots, X_{Ak}(t)) - X_B(t)]\Delta t \quad (4)$$

, where X_B is a characteristic value for node B, η_B is the speed factor which indicates how fast this node can change its value, and c_B is a combination function which takes into account the influence of all nodes $A1,...,Ak$ connected to B, with k being the degree of node B, as shown in Equation 5.

For our simulations, we used the advanced normalized sum combinational function c_B, **adnorsum**, shown in Equation 6.

$$c_B(\omega_{A1,B}(t),\ldots,\omega_{Ak,B}(t)) = \mathbf{adnorsum}(\omega_{A1,B}(t),\ldots,\omega_{Ak,B}(t)) \quad (5)$$

$$\mathbf{adnorsum}(\omega_{A1,B}(t),\ldots,\omega_{Ak,B}(t)) = \frac{\sum_{i=1}^{k} X_{Ai} * \omega_{Ai,B}}{\sum_{i=1}^{k} \omega_{Ai,B}} \quad (6)$$

As before-mentioned, two characteristics are considered and expected to influence the interaction between the individuals in the network: language skills and religiousness. Other aspects could be possibly included in order to make the model more realistic, but for the sake of simplicity we only considered these two states for evaluation. We also believe that the inclusion of new states would possibly enrich the model and could be an interesting exploration for future work.

Next, we have studied different scenarios combining both aspects in the integration of the refugees.

4 MODEL SIMULATIONS AND DISCUSSION

This section presents the results for the simulations performed considering the model presented. As we have two traits affecting the nodes through social contagion and the homophily effect changing the weights of the edges, we divided the simulations in order to better comprehend the outcomes. Important parameters were initialized with certain values in order to obtain results as close to reality as possible. These last are: the number of nodes, the time window frame, the step size and the speed factors. The number of nodes was kept low, having 300 non-refugees and a certain number of refugees appearing in the population. This last number can, of course, be adjusted to simulate different case scenarios by, for instance, getting the percentage of refugees in a specific country. As the proposed model here is a general one, we have not set values related to any specific society. The time frame has a value of 36, and the step size is 1. These values are representing a time step of a month, and it is assumed that within 36 months each person interacts with others at least each month. The speed factors for both the nodes and the edges update is kept at 0.1 since it is considered that religiousness, language and relationships change slowly over time. Here, one must bare in mind that relations are also affected by the local search method which runs without any speed factor. The speed can actually be expressed inside the increase rate δ: the lower it is, the slower the relationships are being incremented.

During the lifetime of the simulation, some random nodes of the network have the chance to be deleted from it and 'move away' from our observable world. Despite their disappearance, these nodes are represented in the output graphs, because they play their role in the evolution of the overall relationships and node state values, regardless of their significance. It can be observed that, in the output graphs of the node state and weight values throughout time, some lines are abruptly cut at specific points. That means that a node has been removed from the network, alongside with its links. This can be correlated to real-life phenomena, such as a person moving away from a society or even unfortunately passing away. Similarly, some lines might appear at time points which are different from zero. Of course, this is an expected behavior because each time a node is deleted, another one is added in the following step. The addition of these nodes prevents the shrinking of the network, which would be inevitable if the nodes kept being deleted throughout a large number of steps.

4.1 Scenario 1 - Language Proficiency and Homophily

In this scenario, we excluded the effect of religiousness as we are interested in knowing what happens with the population of refugees over time concerning their language skills, and how is the integration based only on this trait.

The output plots for the language skill evolution over time are shown in Figure 3 (left). One can see that most of the refugees are improving their language skills and are fully integrated in society. Nonetheless, if the number of refugees is increased, then it is expected that some of them will not be able to be integrated in the society: at least not as quickly. In fact, it can be observed that many of them remain isolated without the ability to get integrated.

Figure 3 (right) shows the evolution of the weights throughout time. As a reminder note, the lines that were abruptly cut represent the node deletions. So as not to visually damage the plots, it was decided not to show whenever these values drop to 0 from one

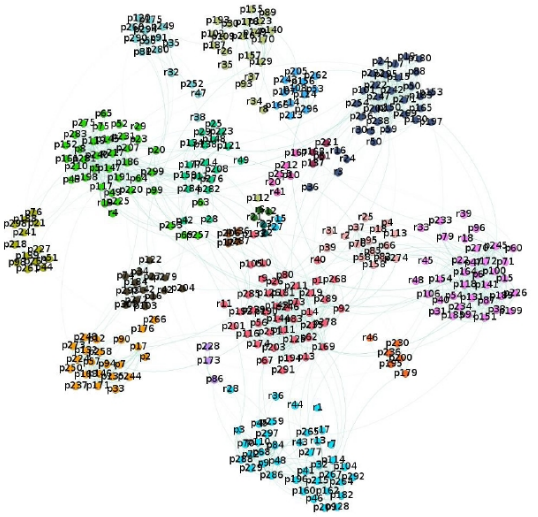

Figure 2: The final graph produced for language skills after running the simulation.

simulation step to the other. Note that similar results from the ones obtained in Figure 3 are valid for this algorithm for whichever size of population.

Figure 2 shows the resulting graph of this network. Some refugees are integrated in the social network, although others are isolated, such as nodes r6, r12 and r21 (in dark green).

4.2 Scenario 2 - Religiousness and Homophily

Now, the effect of language skills is excluded as we are interested in discovering what happens with the population of refugees over time concerning their religiousness, and how is the integration done based only on this trait.

The node and edge updates are shown in Figure 4. The results are analogous to the ones of languages skills, except for the fact that now the values of religiousness converge towards the most common values. Nonetheless, some refugees remain isolated and still hold a quite stable value for their religiousness. A speed factor of 0.05 was used for the homophily effect.

As it can be seen, the node values for the refugees have dropped considerably within the simulation time, whilst the local community remained with values rather unchanged, or very little. The religiousness of the former group tends to go down after the social network is run as expected. However, it is also expected that this parameter does not fluctuate as much as language skills, for instance. The refugees' level of religiousness tends to go down after their integration in the society and thus, interacting with the local community, which in turn has smaller religiousness values. Furthermore, the religiousness values of the local community had very little variation in time, which is explained by the combination of the low speed factor for the node values update and the less influential presence of the refugees if compared to the total number of locals in the society. Note that similar results from the ones obtained in Figure 4 are valid for this algorithm for whichever size of population.

Table 2: Degree distributions of the refugee nodes.

Degree	1	2	3	4	5
Refugees (%)	10	20	40	20	10

In Figure 5, the final graph of the second scenario is shown. It is thus now harder to identify the location of these refugees, which confirms that most them managed to integrate in the network.

4.3 Social Network Analysis

The aim of the present section is to obtain relevant statistics of the proposed network. We built a model of 300 local individuals and 10 refugees being inserted in the society. These individuals are distinguished by their labels 'p' and 'r', respectively. Religiousness is specifically taken into account, where high values are observed virtually only by the refugees, even after running of the algorithm. However, certain local individuals were observed to have increased their religiousness values through the interactions in the social network. High values are mainly observed around the refugee nodes, which explains that the homophily effects were significant enough to alter node values. In Table 2, the degree values of the nodes are depicted against the number of occurrences. The degree values are representative of how connected they are to the network.

The overall average degree was observed with value 10.26. As expected, the curve follows a rather downward exponential distribution, with a few outliers present around the theoretical curves (i.e. the occurrences with values 1, 2 and 3). This result is approximately close to a power law distribution, which indicates that our network is close to being scale-free. Table 2 shows the results for the refugee population.

The next step is to obtain the centrality of nodes in the network, thus, the relative importance of the nodes is obtained. In the model, we defined that a stabilized model is one that follows certain properties, such as being scale-free and having the shortest path-length with rather low values. The average path length had a value of 3.75. The eccentricity distribution was also calculated, which measures the distance from a given

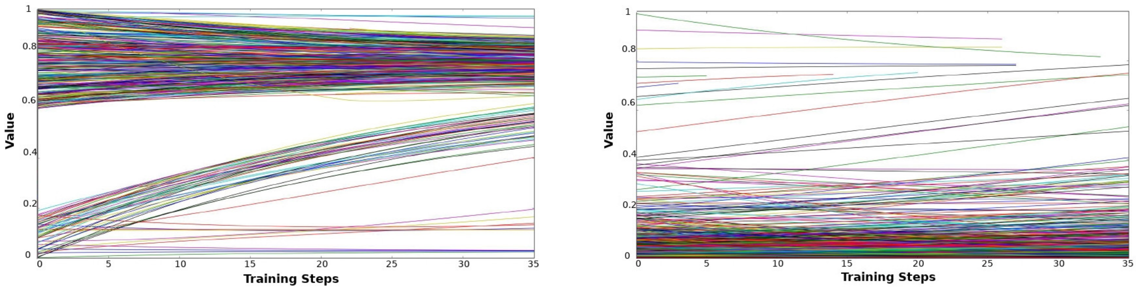

Figure 3: Evolution of language skills (left) and connection weights (right) in a population of 350 nodes, among which 50 are refugees using adnormsum for (left) and advanced quadratic functions for (right).

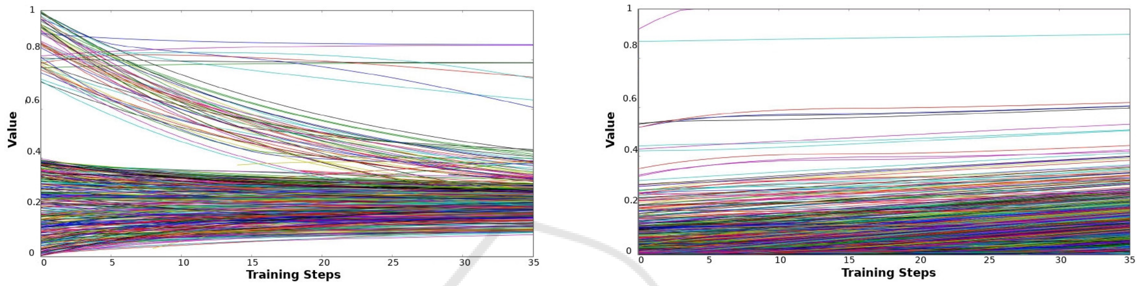

Figure 4: The evolution of religiousness for each node using adnormsum (left) and for the connection weights for each pair of connected nodes using advanced quadratic as combination function (left).

starting node to the farthest node from it in the network. The biggest proportion of the individuals in the network have eccentricity distribution values around 8, which indicates that this same number of individuals are needed to connect the respective node to another extreme of the network. However, a few occurrences needed a much larger number of connections to reach these same extremities. Table 3 depicts the eccentricity values for the refugee population.

In Figure 6, eccentricity values are shown within the network. The nodes in dark gray and pink are those with highest eccentricity values. Surprisingly, these individuals are not refugees, and we obtain here interesting results which show that these last were categorized in another set of values, mostly 7,8 and 9, as shown in Table 3. Even though these eccentricity values are somewhat high, they are representative of the success of our algorithm to integrate these individuals in the society.

Regarding the different communities, as the social network is formed, the initial refugee community is expected to spread as the connections with local individuals develop. A total of 14 communities were observed and the smallest and biggest ones had 2 and 56 members, respectively. One interesting observation is that the refugees were now spread around in the network: in certain communities, there were occurrences of a single refugee present. In others, not many coexisted. The task of integration has been successfully carried out by implementing both algorithms at the same time. Finally, so as not to render this section exhaustive, only religiousness was considered, given that similar trends for language skills are expected, except from the fact that these last are expected to increase as the homophily effects take effect in the algorithm. Furthermore, as the speed factor for language skills is considerably higher, higher degree distributions and lower eccentricity values are expected if compared to religiousness.

5 PARAMETER TUNING

The second part of the overall analysis of the model behavior is focused on validating the proposed model through parameter tuning. Due to the fact that any model must be a close approximation to the real-life phenomenon that it corresponds to, it must be “tuned” in such a way that it is as representative and reliable as possible. This is done through choosing specific parameters and applying optimization techniques upon them in order to obtain the best corresponding values.

For that reason, these techniques are based on some empirical data that is given as an input and is compared to the observed data that the model outputs. The main goal is to obtain as little erroneous behavior as possible, with the error being defined as the mean squared error between the simulated and the empirical

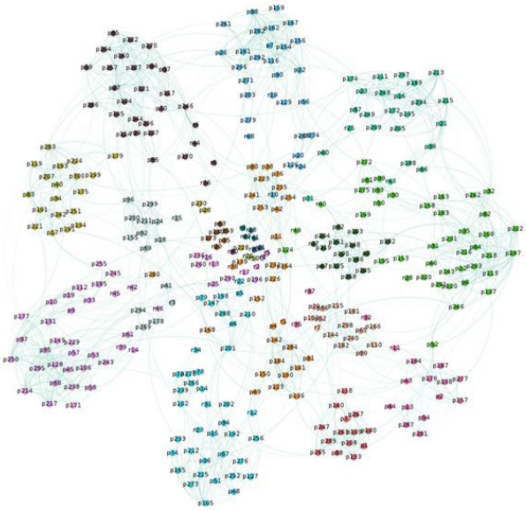

Figure 5: The final graph produced for religiousness after running the simulation.

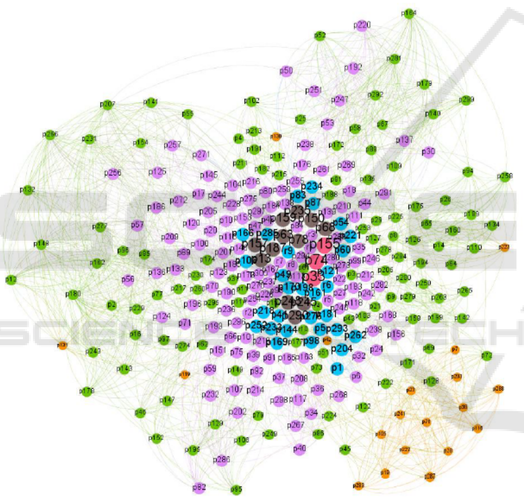

Figure 6: Eccentricity of religiousness in the social network.

Table 3: Eccentricity distributions of the refugee nodes.

Eccentricity	7	8	9
Refugees (%)	20	60	20

values.

Simulated annealing (Eglese, 1990) is used to fine-tune the model and make it more representative and reliable. Pseudo-empirical values of the state and weight values of the population were created, as the extraction of reliable related real data was hard. As it is known, simulated annealing combines the advantages of gradient descent and random walk in such a way that it assures efficiency and completeness. Three parameters of it are crucial for its outcome on parameter tuning optimality: the temperature T, the minimum temperature T_{min}, the parameter α, the maximum number of iterations i, and the definition of the acceptance probability. The temperature T is normalized between the values 0 and 1, and consequently the starting value T is set to 1. At each step, T is multiplied by α, shrinking the value and getting closer to T_{min}, which is set to 0.001. We set value α to be 0.9, which guarantees to give a satisfactory number of iterations which would lead to optimal results, however sacrificing run time. The number of iterations at each temperature step is set to be 100. Finally, the acceptance probability method is given based on the values of the temperature, the new cost and the old cost, where *new cost* $>$ *old cost*. Even if the new cost is higher than the older cost, it is accepted with the following acceptance probability:

$$P_{acceptance} = e^{-\frac{newcost - oldcost}{T}} \quad (7)$$

All the above parameter values are believed to give the best expected results, or at least results with a neglibilble arbitrary error. The pseudo-data was extracted by adjusting the original model parameters in such a way that the output seems as realistic as possible. For instance, we adjusted the speed factor and the rest of the functional parameters in a way that the religiousness of refugees would slowly decline over time. As the time frame is set to show three years, it is believed that the religiousness of refugees would not be totally adjusted to the general population, since it is a characteristic that is deeply rooted and it is not expected to change significantly. The extracted pseudo-empirical data consists of '.csv' files which contain the values of the states and the edges throughout time. In order to simplify the procedure of simulated annealing in terms of run time, these values were extracted in each 6 time steps, starting from time points 0 and 5 and moving on to points 11, 17, 23, 29 and 35. We chose a small number of parameters in order to obtain results within reasonable time, and excluded the error calculation between edges values, as this would make the program run within unreasonable time. Nevertheless, it can be easily extended by adding more parameters and adjusting the error calculation.

The initial parameters chosen were the speed factor and the threshold used within the functions that apply the homophily principle. The speed factor is used by both combinational functions in the edge update and the node update, respectively, and is set to an initial value of 0.5. The threshold value is used by the edge update's advanced quadratic function and is also initially set to 0.5. After running the simulated annealing for a model based on the language level of 2 refugees among a society of 10 non-refugees, we obtained satisfactory results. The final run of the model under simulated annealing gives a diagram for the evolution of the node states which is depicted in Figure 7. The x-axis gives the time frame measured in months. In this particular instance, one can see that the refugees are fully integrated after the 25th month. This model is really close to the one obtained by the empirical data.

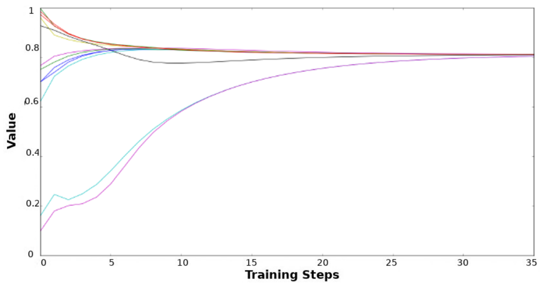

Figure 7: Evolution of language skills after parameter tuning through simulated annealing.

6 CONCLUSIONS

The present work aimed at studying the integration of refugees through the implementation of a network-oriented model. Individuals from local communities and refugees were represented as nodes and relationships between them were modeled as edges with weight values varying in time. The significance of each individual was made through values representing religiousness and language skills. As it is a model based in real-life scenarios, these values were created as close to reality as possible, indicating low levels of language skills for refugees arriving in the communities, for instance. Notwithstanding, minimum and maximum values were set, being a constraint for the model.

A model proposed in literature was used so as to build a stabilized network, upon which a dynamic model was implemented in order to render node and edge values dynamic. Two case scenarios were explored, considering two characteristics from the individuals: religiousness and language skills. A set of combination functions were selected so as to implement the evolution of node and edge values within time. Social contagion and homophily effects were best represented by the adnorsum and advanced quadratic functions, respectively, as they were closer to a real-life scenario. Furthermore, node deletion and node creation were both implemented as they are characteristics of a real society: relationships end and start continuously in a population setting. The parameters of the dynamic model were adapted to represent how these interactions evolve in time. It is expected that people interact with each other at least once every 3 years, and speed factors were rather low, as it is expected that language skills and religiousness change slowly with time. Different scenarios were created, in which a certain number of refugees arrive in these local communities. It was observed that integration was observed for most of them, however a part of the refugee population did not manage to become integrated in the society, and levels of language skills and religiousness stayed rather unchanged in time.

A social network analysis was also built, which studied more in-depth the evolution regarding the refugee population. Degree and eccentricity distribution measurements were calculated in order to better understand how integrated these individuals became. Later on, simulated annealing was successfully applied as a parameter tuning technique based on empirical data. The implemented code worked upon the state values and tried to tune both speed factor and threshold, and can be safely extended in the future in order to run upon more parameters and error calculations.

Finally, the present work implemented a methodology of manipulating stabilized networks in order to build case scenarios in which new individuals appear in a much larger setting of people. The interest being to understand how these interactions are built and developed throghout time, the proposed methodology is an efficient and feasible way of studying the integration of refugees in their new communities.

Other interesting scenarios would be to study how the extroversion and openness of both the local population and the refugees would help these last integrate in a society. As explained by (Dinesen et al., 2014), openness has an unconditional effect on attitudes toward immigration: scoring higher on this trait implies a greater willingness to admit immigrants, thus interacting with them once they have already reached their final refuge destinations. Expressiveness would be understood as extroversion, which in the model could be represented as a higher or lower easiness of amplifying one's social network, by i.e. meeting new people and widening contacts within and between communities. Openness and expressiveness values would be compared alongside, which means that the values of one characteristic must be compared to the values of the other one, as it is expected that one's higher extroversion is best match with another's higher openness towards others. Thus, in such scenarios, it is expected that these connections would become stronger with time.

REFERENCES

A. Beaman, L. (2012). Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S. *Review of Economic Studies*, 79:128–161.

Ager, A. and Strang, A. (2008). Understanding Integration: A Conceptual Framework. *Journal of Refugee Studies*, 21.

Beiser, M. and Hou, F. (2001). Language Acquisition, Unemployment and Depressive Disorder among Southeast Asian Refugees: A 10-Year Study. *Social Science & Medicine*, 53:1321–1334.

Beiser, M., Johnson, P., and Jay Turner, R. (1993). Unemployment, underemployment and depressive affect among Southeast Asian refugees. *Psychological medicine*, 23:731–43.

Chaaya, M., Sibai, A., Fayad, R., and El-Roueiheb, Z. (2007). Religiosity and depression in older people: Evidence from underprivileged refugee and non-refugee communities in Lebanon. *Aging & mental health*, 11:37–44.

Collyer, M., Brown, R., Morrice, L., and Tip, L. (2017). Putting refugees at the centre of resettlement in the UK. *Forced Migration Review*, 54.

Dinesen, P., Klemmensen, R., and Nørgaard, A. (2014). Attitudes Toward Immigration: The Role of Personal Predispositions. *Political Psychology*, 37.

Dunn, K. and Horgas, A. (2004). Religious and nonreligious coping in older adults experiencing chronic pain. *Pain management nursing : official journal of the American Society of Pain Management Nurses*, 5:19–28.

Eglese, R. (1990). Simulated Annealing: A Tool for Operational Research. *European Journal of Operational Research*, 46:271–281.

Fasani, F., Frattini, T., and Minale, L. (2018). (the struggle for) refugee integration into the labour market: Evidence from europe.

Korac, M. (2003). Integration and How We Facilitate it A Comparative Study of the Settlement Experiences of Refugees in Italy and the Netherlands. *Sociology*, 37.

Koser, K. (1997). Social Networks and the Asylum Cycle: The Case of Iranians in the Netherlands. *The International migration review*, 31:591–611.

Krahn, H., Derwing, T., Mulder, M., and Wilkinson, L. (2012). Educated and Underemployed: Refugee Integration into the Canadian Labour Market. *http://lst-iiep.iiep-unesco.org/cgi-bin/wwwi32.exe/[in=epidoc1.in]/?t2000=025393/(100)*, 1.

Kuhlman, T. (1991). The Economic Integration of Refugees in Developing Countries: A Research Model. *Journal of Refugee Studies*, 4.

Page, E. (2016). European Commission Statistics Agency Eurostat (2016) Asylum quarterly report. http://ec.europa.eu/eurostat/statistics-explained/index.php/Asylum_quarterly_report. Accessed: 2017-05-22.

Puma, J. E., Lichtenstein, G., and Stein, P. (2018). The rise survey: Developing and implementing a valid and reliable quantitative measure of refugee integration in the united states. *Journal of Refugee Studies*, 31(4):605–625.

Rapoport, A. (1957). A Contribution to the Theory of Random and Biased Nets. *The Bulletin of Mathematical Biophysics*, 19:257–277.

Ryan, L., Sales, R., Tilki, M., and Siara, B. (2008). Social Networks, Social Support and Social Capital: The Experiences of Recent Polish Migrants in London. *Sociology-the Journal of The British Sociological Association - SOCIOLOGY*, 42:672–690.

S. Granovetter, M. (1983). The Strength of Weak Ties: A Network Theory Revisited. *Sociological theory*, 1:201–233.

Sharpanskykh, A. and Treur, J. (2014). Modelling and Analysis of Social Contagion in Dynamic Networks. *Neurocomputing*, 146.

Sheikh, M. and Anderson, J. R. (2018). Acculturation patterns and education of refugees and asylum seekers: A systematic literature review. *Learning and Individual Differences*, 67:22–32.

Strang, A. and Ager, A. (2010). Refugee integration: Emerging trends and remaining agendas. *Journal of refugee studies*, 23(4):589–607.

Toivonen, R., M. Kumpula, J., Saramäki, J., Onnela, J.-P., Kertész, J., and Kaski, K. (2007). The role of edge weights in social networks: modelling structure and dynamics. *Proc SPIE*, 6601.

Treur, J. (2016). *Network-oriented modeling*. Springer.

W. Berry, J. (2001). A Psychology of Immigration. *Journal of Social Issues*, 57:615 – 631.

Williams, L. (2006). Social Networks of Refugees in the United Kingdom: Tradition, Tactics and New Community Spaces. *Journal of Ethnic and Migration Studies - J ETHN MIGR STUD*, 32:865–879.