# Agent based model of anger contagion and its correlations with personality and interaction frequency

Mara Pudane, Bernard P. Brooks, Rebecca J. Houston, and Michael A. Radin

Abstract— The research interest of the paper is investigating how various factors impact annoyance and anger propagation in the network. In general, emotion in a human network propagates via process that in psychology is called emotional contagion. While there already are attempts, some very elaborate, to model emotion contagion, to authors' knowledge none of them look at it as depending on interaction time. To perform simulations, an agentbased model was developed based on real data. The model allows to input personality and interaction frequency as parameters. As a result, some unintuitive results were acquired. First, it was assumed that maximum anger intensity in the network will grow linearly with Neuroticism value, however, the results showed sigmoid character. Secondly, it was also assumed that depending on interaction time, the decrease will be linear but the simulations show very slight decrease or even peak at the beginning. One of the tasks to supplement this research is measuring and confirming the existence of such predicaments in real life.

*Keywords*—Agent based simulation, multi agent system, anger, violence, network, semi-dynamical system.

### I. INTRODUCTION

A NGER is one of the most researched emotions due to its consequences that may be downright disastrous in cases of violence [1] and visible displays that enable anger inducing and observation [2]. Moreover, anger is influential emotion in a human group. There is scientific evidence that emotions are passed from person to person. The process of subconscious emotion passing is called primitive emotional contagion; it is based on mimicking other's emotional displays [3].

It has been emphasized in multiple literature sources that for human group behaviour modelling, agent based modelling should be used as opposed to equation based modelling [2, 3].

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M. Pudane is with Department of Artificial Intelligence and Systems Engineering, Riga Technical University, 1 Kalku str., Riga, Latvia (phone +371 67089529, e-mail: <u>mara.pudane@rtu.lv</u>).

B. B. Brooks is with School of Mathematical Sciences, Rochester Institute of Technology, Rochester, New York 14623 U.S.A. (e-mail: <u>bpbsma@rit.edu</u>).

R. J. Houston is with Health and Addictions Research Center, Department of Psychology, Rochester Institute of Technology, Rochester, New York 14623 U.S.A. (e-mail: <u>rjhgss@rit.edu</u>).

M. A. Radin is with School of Mathematical Sciences, Rochester Institute of Technology, Rochester, New York 14623 U.S.A. (e-mail: marsma@rit.edu).

Agent based models (ABM) are by far the most efficient mathematical modelling technique to incorporate the knowledge of subject experts, such as psychologists (e.g., as in [6]). An ABM consists of agents following a set of rules governing their behaviours as functions of their environment and the states of the agents with whom they interact. Subject experts can more easily inform those rules and produce a more realistic model than would be found using other techniques; since other modelling techniques such as systems of partial differential equations present a mathematical barrier between the subject experts and the model. Complex behaviours of the overall system and feedback can emerge that are not obvious in models that only consider individual agents.

The model presented here simulates anger flow on a social network. The agents are the people connected in a social network. The states of the people change as the emotional contagion flows over the network according to the ABM rules informed by real life psychological principles.

The paper is structured as follows: Section 2 presents related work, Section 3 describes method from a single and multiple agent perspective, as well as relevant method implementation details. Section 4 discusses results. Finally, conclusions are made and future work highlighted.

### II. RELATED WORK

Since the research is interdisciplinary, the related work is split into two parts. First, anger is reviewed from the perspective of psychology. Then, the related computational models are reviewed.

### A. Measuring anger

Anger is "an emotional state that consists of feelings that vary in intensity, with associated activation or arousal of the autonomic nervous system" [7]. Since the main aim of the model is to create a believable representation of emotion propagation, we thus focus on the categorical emotion view [2], still defining anger as a category of emotions with low valence, yet high arousal and dominance [8].

The personality of the people involved influences the emotional contagion in general as well as emotional intensity level of an individual. Personality in primitive emotion contagion impacts two things, namely, how fast does the emotion spread (i.e., the expressiveness of emotion) and how deep is the impact of an emotional contagion (i.e., susceptibility) [9]. Although some of the related works consider personality as expressiveness and susceptibility variable (e.g., [10]), these models do not explain what types of personalities have high or low susceptibility, as well as what kind of personality traits impact these factors.

The Big Five model is currently the most used and best verified model that allows modelling personality as a combination of five traits: Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism [11]. The usage of such a psychologically grounded model would enable better exploration of a group of humans as there is extended research based on this model that explores personality impact on group dynamics [12].

While there are five traits in this personality model, not all of them impact emotions equally. For anger, the highest correlation has been found in the Neuroticism trait; anger also correlates negatively with Agreeableness [12, 13]. The work of Pease and Lewis is built on the State-Trait Anger Expression Inventory (STAXI), which differentiates among various parameters of anger including trait anger, which is person's general predisposition to become angry, and Anger Expression Out (A-Out), which reflects extent to which person expresses emotional state [14].

We use the trait anger to implement how quickly and intensely a person gets annoyed and A-Out (anger expression power) to implement how intensive will be outward signs of anger [14].

## B. Computational anger propagation models

There are two types of computational models that can be applied as anger models. First, models that aim at modelling emotions in general, not focusing on a particular emotion. Secondly, there are models that model anger in particular, mostly as one of multiple emotions.

One of the models that belong to the first group, is developed by Bosse et al. [10]. This research includes a mathematical model of the spiral effect (i.e., the property of emotion amplifying when passed from person to person) in group dynamics. The model of separate group members is also very elaborate and includes not only some personality factors of group members (e.g., expressiveness) but also multi-weighted relationships amongst the people [10]. The model also provides mathematical analysis of an emotional contagion. As the authors themselves notice though, the model focuses on only one type of emotion; it also is not based on real-life sets and thus is does not allow one to make conclusions from a psychological perspective.

The second group includes more models, such as the one developed by Bispo and Paiva [10]. The model includes expressiveness and energy (power of expression which strongly correlates with arousal) of emotions. The anger was modelled as a high energy emotion, same as joy. The model is appended in [15] to be more generic and include larger population data. The method used in this model does not correspond to results found in social network analysis in the paper [16] that found anger to be more easily passed. The authors of this paper believe that the difference occurs due to the parameters of the agents, namely, the personality differences that were minimized.

Emotional contagion has been researched in crowd modelling scenarios. One such model included teaching soldiers how to prevent a crowd from becoming unpredictable and uncontrollable by simulation [17]. The model is appraisal based and well-grounded in psychology, however, it does not make a distinction between felt and expressed emotion: an agent directly expresses its internal state. Agents have three types of personalities that impact susceptibility threshold [17].

In summary, while there are several models that simulate emotional contagion, they either lack believability, i.e., are not based on ground truth data, or personality impact is excluded (or minimized). In psychology however, on various occasions the impact of personality has been stressed. For example, a significant literature exists demonstrating the association between neuroticism and physical aggression [1, 18].

# III. Method

The method consists of two parts. First, single agent architecture and affective state calculations are explained. Then, issues regarding agent interactions are defined and discussed.

# *A.* Anger dynamics function calculations within a single agent

Within single agent intensity of anger dynamics is calculated based on three intertwining functions.

First, there is an activation function that determines the relationship between the objective irritation strength and the subjective anger intensity level. For modelling this function, several options have been proposed, such as linear or exponential [19], however, it has been noted that sigmoid is the most believable [19, 20] due to repeated strike (multiple small irritations induce more intensive feelings than one larger irritation) and saturation properties (1).

$$I(subj) = \frac{AngTN}{1 + e^{\frac{-(I_{obj} - x_0)}{s}}}$$
(1)

The semantic background for the activation function was Trait anger from STAXI; the data for Trait anger in relation to Neuroticism (denoted by *AngTN*) was acquired in Pease's and Lewis's work [12]. The relation between these scores was assumed to be linear (2).

$$AngTN = 0.95926 * N + 0.11563$$
(2)

By knowing when the sigmoid should start saturating,  $x_0$  and *s* values were calculated. Parameter s determines steepness (3),  $x_0$  – the starting point of the sigmoid (4).

$$x_0 = \ln 999 * s \tag{3}$$

$$s = \frac{-maxY}{\ln 0.001 - \ln 999}$$
(4)

Parameter maxY denotes maximum achievable anger level based on personality and was calculated as linear correlation of s and  $x_0$  parameters (5).

$$maxY = -0.7 * AngTN + 1.2 \tag{5}$$

Secondly, there is decay function that determines how fast emotion will pass. On multiple occasions both in psychology [21] and in computer simulations [22] it has been determined the most believable character for decay is exponential so exponential function was used here as well (6). Decay function parameters (i.e., time of decay) were extracted based on Codispoti's et.al. work [23] (7).

$$I_{subj} = e^{\frac{\ln(0.01)}{\operatorname{angDecayTime}^{*t}}}$$
(6)

angDecayTime = 30 \* (1.89444 \* N - 0.06292)

(7)

(8)

Finally, the expression function was defined. It determines what will be internal affective state relation to anger outward expression [6, 10]. Sigmoid was chosen due to saturation properties. Again, it was assumed the correlation between neuroticism N and Anger Expression-Out values are linear. The formulas used were identical to activation function except instead of trait anger, *AngTN*, Anger Expression-out value *AngON* was used (8).

AngON = 1.11485 \* N + 0.07318

Functions intertwine in following way (see Fig.1): first, when a subjective irritation comes in, if the anger state is 0, the activation function is used to calculate the subjective intensity. If subjective intensity does not equal zero, the remaining "objective" irritation is calculated and summed with incoming irritation. This ensures repeated strike property. Then, if incoming irritation is above the susceptibility threshold, decay starts. Parallelly, the emotional intensity is passed to the expression function to calculate power of expression. The output becomes the new objective irritation.

Similarly as in other related works [10, 17], the susceptibility threshold was defined. The threshold here depends on Neuroticism of the agent and varies around 0.03.

### B. Anger propagation modelling

Anger propagation modelling from inter-agent perspective consists of three parts (1) choosing network structure (2) determining interaction frequency among agents (3) deciding on the output of the model.

The network over which the emotion will flow is first

created using preferential attachment algorithm [24] with n people as the nodes. Preferential attachment was chosen because it produces a scale free network with many people having a few links to others and a few people having many links to others. Such a network provides a realistic simulation of an actual social network. Once the network is created one node is chosen as the initial flash point, that person is annoyed by an outside stimulus. The network is directed so interaction among two people only happens one way.

To determine interaction frequency among agents, the Poisson distribution was chosen [25]. This discrete probability distribution allows the calculation of the probability with which an event will happen in the given time span. Since the agent's affective dynamics are running real-time, it is not needed to split seconds and thus discrete distribution works well.



Fig 1. Affective state dynamics within agent



Fig 2. User interface in the tool, on the left – main window, on the right – visualization.

Finally, to measure annoyance level of the network, average anger level of all agents was measured. It was obtained by calculating mean state of all agents' anger levels every time moment. Maximum achieved anger level was measured as model output.

### C. Implementation

The model was implemented in JADE by using multi-agent system mechanisms. JADE is middleware platform based on Java that is then used for multi-agent system implementation. The solution developed in this research allows changing agent parameters (such as personality traits) as well as generating various network structures.

Fig 2 displays the user interface of developed tool. On the left side main window is displayed. Anger propagation parameters such as initial irritation level and irritation frequency are entered here. The program outputs numbers of nodes that are angry as well as first infected agent's internal anger intensity level and anger expression level (in the upper chart in main window). The lower chart in the main window represents network mean anger intensity over time.

# IV. RESULTS AND DISCUSSION

The results of the paper are analysed from two points of view: (a) how Neuroticism impacts anger propagation (Fig 3) (b) the character of graph from the perspective of how interaction time impacts maximum anger (Fig 4).

The experiments were carried out in the following way: the initial agent was annoyed 5 times every three seconds with

irritation value 0.5 so that initial agent would achieve maximum anger value available to him. Network consisted of 52 vertices of which 2 were defined as central nodes when network was generated. At each step of network generation two edges were added.

In the (a) case, we expected a linear decrease, however, the results show that from 0-2 sec there is no difference in maximum average anger value, the anger might even display a peak value at 2 seconds, then the slope becomes steeper thus acquiring exponential character.

In the (b) case we expected a linear dependency since the maximum available intensity for agents differs based on their Neuroticism values, however, anger intensity changes in a sigmoid. For 2 seconds, the sigmoid is so steep it creates a threshold. According to data Pease and Lewis [12] provided, with interaction time 2 s (intensive interaction) the threshold appears when Neuroticism is above average.

### V. CONCLUSION

The paper presents the anger propagation model. While the model already allows determining relations of neuroticism and average interaction time to average anger intensity in the network, the authors plan to continue this research.

While one might argue that the fact graph is oriented decreases believability of the model, preliminary simulations showed bidirectional graph shows different patterns and additional parameters (such as tiredness of argument) should be included. For this reason, bidirectional graphs remain next step in this research.



Fig. 4 Anger dependency on Neuroticism in various interaction times. When t = 2, in a measured precision a threshold appears, thus, in intensive communication agents with lower N might achieve higher intensity levels than agents with much higher N when t = 4.

Some unusual empiric observations were made while performing simulations in the model – one of the nodes frequently was the last to "calm down". Our hypothesis is, that is related to network structure. Thus, investigating different network structures also is intended.

The average anger level is not the only thing that can be measured. Time moment when the maximum level of anger was acquired as well as the duration of affective state in the network can be measured.

Finally, the rules governing the agents' behaviours are grounded in psychological principles and their interactions in this complex system produced a non-intuitive result, namely the peak in the anger level (Fig 4) and threshold when interaction time equals 2 (Fig 3). Could psychological experiments be created that measure and confirm the existence of such a predicted peak value and threshold?



Fig 3. Anger dependencies on interaction time; in (a) N = 0.3 and the peak can be seen better. In (b), (c), and (d) the maximum intensity values of 2 and 4 are equal, almost equal or value at 4 is even higher.

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