Part IV

Use of Contagion Models for Perceptions and Emotions

"And may I ask, oh, Lucy Daughter of Eve," said Mr. Tumnus, "how you have come into Narnia?"

"Narnia? What's that?" said Lucy.

"This is the land of Narnia," said the Faun, "where we are now; all that lies between the lamp-post and the great castle of Cair Paravel on the eastern sea. And you– you have come from the wild woods of the west?"

"I– I got in through the wardrobe in the spare room," said Lucy.

C.S. Lewis, *The Lion, the Witch and the Wardrobe (1950)*[1]

A Temporal-Causal Model for Spread of Messages in Disasters[1]

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> *"I have received no assurance that anything we can do will eradicate suffering. I think the best results are obtained by people who work quietly away at limited objectives, such as the abolition of the slave trade, or prison reform, or factory acts, or tuberculosis, not by those who think they can achieve universal justice, or health, or peace. I think the art of life consists in tackling each immediate evil as well as we can."*
>
> — **C.S. Lewis**
> "The weight of glory"[2]

Abstract

In this paper we describe a temporal-causal model for the spread of messages in disaster situations based on emotion contagion and awareness works. An evaluation of the model has been done by simulation experiments and mathematical analysis. Parameter tuning was done based on two scenarios, including a credible message and a dubious message. The results are useful for the prediction of reactions during disasters, and can be extended to other applications that involve panic and supportive systems to assist people.

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9.1 Introduction

The possibility of disaster and tragedy are a constant in everyone's lives. Apart from the problems caused by humans themselves (due to political decisions, errors, etc.), natural disasters also frequently occur in many places on Earth.

In 1953, a flood was caused by an extremely heavy storm in the Netherlands, England, Scotland and Belgium, called the North Sea Flood [4]. In the aftermath of this disastrous flood, a protective construction in the form of the Delta Works was created in the Netherlands in order to protect the country against similar natural disasters. Despite the protection of this new construction, a new flood is still a possibility. This was shown in a Dutch TV series called 'Als de dijken breken', or directly translated, 'If the dikes break'. This series raises the question of whether people are prepared for such a natural disaster [6]. What makes the scenario of 1953 different from nowadays is the current use of technology for communication. During the Twin Towers attack on the 9/11 in 2001 in New York, survivors made phone calls during the evacuation, most of which were not directed to emergency personnel, but to relatives, friends and family [1].

The spread of information in emergency situations can bring panic or can calm people down, like for relatives and friends that would remain in a stressful state in case of a lack of information about someone involved in a tragedy. In order to understand this scenario, we propose a temporal-causal model that considers how the act of sending a message could influence people's behaviour through social contagion. Some of the questions that guided us are related to how the information (message) is received. How people react regarding to the context, the sentimental and the emotional charge of the message? Are they unable to perform any action, or intentionally not taking action when the message is not taken seriously? Does the source and the type of communication define if the message is serious or not?

In section 9.2 we discuss the background theory. Section 9.3 discusses the temporal-causal network model in detail, with both a conceptual and a numerical representation. Section 9.4 is dedicated to the parameter tuning and datasets. In section 9.5 are the simulation results in multiple scenarios, and the mathematical analysis. Lastly, section 9.6 will be the discussion of the paper.

9.2 Social Contagion and Behaviour in Disaster Situations

Modeling disaster situations is a huge challenge. Especially, because it is impossible to simulate realistic scenarios for this sort of event. Because of this, our model considers similar situations and combines different works that explain parts of the cognition of humans and presents some solid ground to build upon.

Blake et al. [1] studied the reactions of survivors of the World Trade Center attack on 9/11, in 2001. Over 20% of the survivors that participated in his research had made phone calls during the evacuation, and 75% of these calls were directed to relatives, friends and family, and not emergency personnel. The survivors wanted to inform their relatives about the situation, their whereabouts and warn them about what was going on. They also used the calls, text messages and emails (on Blackberry devices) to gather more information on the situation from outside during the evacuation process. In our model we consider the emergence of social media as a trend, and possibly an easy way to communicate with people during a disaster.

Paton [5] developed a model of disaster preparedness using the knowledge about the social cognitive preparation system. This model describes how people prepare for disaster situations that might occur in the future and how different factors can affect that process. The focus on disaster situations in the future is different from our approach as we want to look into the spontaneous occurrence of a disaster and how people respond here. Paton shows that there are clear indications that anxiety or fear can play a motivating or demotivating effect in preparing for a disaster.

Bosse et al. [2] propose a temporal-causal model for emotion contagion based on interaction between individuals. It shows how specific traits of people define how they affect each other. For our model we assume that the messages, used to communicate, carry some subjective content. This can be seen as the sentiment of the message. Furthermore, it carries other cues to which the cognitive system will pay attention on the attempt to unfold and understand, for instance, how serious the message is.

Thilakarathne and Treur [8] present a computational agent-based model to simulate emotional awareness and how this may affect the execution of an action. Thilakarathne and Treur [7] also introduce a neurologically inspired agent model which makes distinctions between prior and retrospective awareness of actions. Those concepts are used in our model, as a way of tracking awareness in our agents who will receive messages. Our model follows the Network-Oriented modeling approach, proposed by Treur [9].

9.3 Agent-based model

This section presents the designed temporal-causal model. The numerical representation for the connections in the network is also shown. This model represents a scenario where the person has a perception of the environment, and starts receiving messages from another person about a possible disaster happening. The internal states are based on the emotions and potential actions of the person. Figure 10.1 shows the conceptual representation of the temporal-causal model.

Table 9.1 describes the meaning of each state in the model. We based our model on the previous models by Thilakarathne and Treur [7] and Thilakarathne and Treur [8], but without the element of ownership. In addition, the model has been extended in the field of emotion and sentiment, both positive and negative. Despite the fact that we realize culture could be of some influence, we decided to not include this in the model.

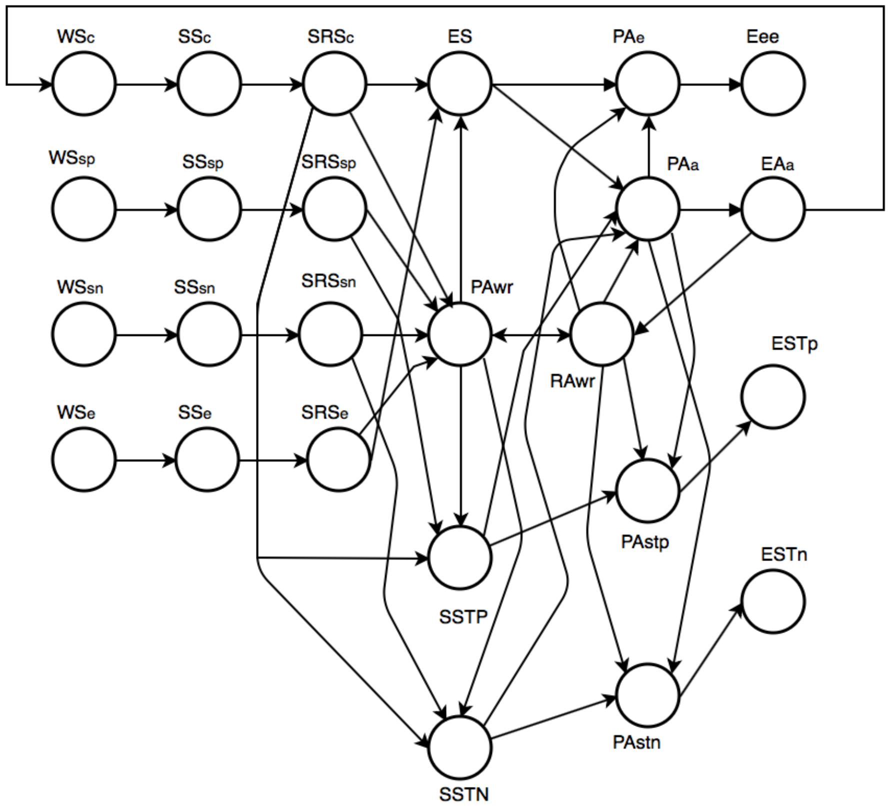

Fig. 9.1: Temporal causal network model

The scenario for this model can be understood as someone who receives a message claiming that something bad is happening, and the person starts to investigate the environment to see if there is any cue that matches the message. It can be an alarm message about a storm approaching. In this case, the perceptions about the environment could come from taking a look outside of a window.

The model has four different world state inputs. The critical awareness of hazards [5] are represented as the world state *context* (the environmental context at the moment) WS_c. In order to include the anxiety factor, we added emotion (scariness, shock, excitement and shame, based on Ekman's basic emotions [3]), positive sentiment and negative sentiment, respectively as world states WS_e, WS_{sp} and WS_{sn}.

These external inputs are then sensed and lead to the sensor states SS_c, SS_{sp}, SS_{sn} and SS_e. Subsequently they proceed to the sensory representation states, SRS_c, SRS_{sp}, SRS_{sn} and SRS_e, which indicate how intense the stimuli is perceived by the person.

The emotional state ES is the current emotional state of the person, influenced by the *context* and *emotion* stimuli. The prior-awareness $PAwr$ is the awareness state of a person before they have executed any action. The $PAwr$ can then be suppressed by the retrospective-awareness, $RAwr$, when the person actually has executed an action which might have changed their awareness state. The two states for the sentiments are the positive, $SSTP$, and the negative state, $SSTN$. These two states

Tab. 9.1: External and internal states of the model

Notation	Description
WS_c	World state context *c*
WS_{sp}	World state sentiment positive *sp*
WS_{sn}	World state sentiment negative *sn*
WS_e	World state emotion *e*
SS_c	Sensor state context *c*
SS_{sp}	Sensor state sentiment positive *sp*
SS_{sn}	Sensor state sentiment negative *sn*
SS_e	Sensor state emotion *e*
SRS_c	Sensory representation of context *c*
SRS_{sp}	Sensory representation of sentiment positive *sp*
SRS_{sn}	Sensory representation of sentiment negative *sn*
SRS_e	Sensory representation of emotion *e*
ES	Emotion state
$PAwr$	Prior-awareness state
$RAwr$	Retrospective-awareness state
$SSTP$	Sentiment state positive
$SSTN$	Sentiment state negative
PA_e	Preparation for action emotion *e*
PA_a	Preparation for action *a*
PA_{stp}	Preparation for action sentiment state positive *stp*
PA_{stn}	Preparation for action sentiment state positive *stn*
EE_e	Expressed emotion *e*
EA_a	Execution of action *a*
EST_p	Expressed sentiment state positive *p*
EST_n	Expressed sentiment state negative *n*

are defined as the current sentiment state of the person, whether the stimuli had a positive or negative sentimental charge.

The model has four similar preparation states. The state preparation of a person to express an emotion, PA_e, leads to the external state expressed emotion EE_e. The state preparation for action PA_a prepares a person to execute an action, which leads to the external state execution of action, EA_a. Lastly, both states preparation for action sentiment state positive *stp*, PA_{stp} and preparation for action sentiment state negative *stn*, PA_{stn}. These two preparation states lead to the expressed sentiment state positive EST_p and expressed sentiment state negative EST_n.

Appendix A (`www.cs.vu.nl/~efo600/iccci17/appendixA.pdf`) shows all connections between the states within the model and where each of the combined functions were used. The temporal-causal behaviour of the model is based on the methods proposed by Treur [9]:

1. At each time point t each state Y in the model has a real number value in the interval $[0, 1]$, denoted by $Y(t)$.

2. At each time point t each state X connected to state Y has an *impact* on Y defined as $\mathbf{impact}_{X,Y}(t) = \omega_{X,Y}X(t)$ where $\omega_{X,Y}$ is the weight of the connection from X to Y.

3. The *aggregated impact* of multiple states X_i on Y at t is determined by a *combination function* $\mathbf{c}_\gamma$**(..)** where X_i are the states connected to state Y.

$$\begin{aligned}\mathbf{aggimpact}_\gamma(t) &= c_\gamma(\mathbf{impact}_{X_1,Y}\mathbf{(t), ..., impact}_{X_k,Y}\mathbf{(t)}) \\ &= c_\gamma(\omega_{X_1,Y}X_1(t), ..., \omega_{X_k,Y}X_k(t))\end{aligned} \tag{9.1}$$

4. The effect of $\mathbf{aggimpact}_\gamma\mathbf{(t)}$ on Y is exerted over time gradually, depending on *speed factor* η_γ

$$\mathbf{d}Y(t)/\mathbf{d}t = \eta_\gamma[\mathbf{aggimpact}_\gamma(t)\text{- } Y(t)] \tag{9.2}$$

5. Thus the following difference and differential equation for Y are obtained:

$$\mathbf{d}Y(t)/\mathbf{d}t = \eta_\gamma[\mathbf{c}_\gamma(\omega_{X_1,Y}X_1(t), ..., \omega_{X_k,Y}X_k(t)) - Y(t)] \tag{9.3}$$

The two combination functions used in our model were the identity and the advanced logistic (alogistic) functions. The identity function is $\mathbf{c}_\gamma(V) = \mathbf{id}(V) = V$, while equation 9.4 shows the advanced logistic function. The results of the simulations are shown in Section 9.5.

$$\begin{aligned}\mathbf{c}_\gamma(V_1, ...V_k) &= \mathbf{alogistic}_{\sigma,\tau}(V_1, ...V_k) \\ &= \left(\frac{1}{1+e^{\sigma(V_1+...+V_{k-\tau})}} - \frac{1}{1+e^{\sigma\tau}}\right)(1+e^{-\sigma\tau})\end{aligned} \tag{9.4}$$

9.4 Data generation and parameter tuning

This section describes which datasets were used to tune the parameters of the model. It is, furthermore, described how the parameters were tuned.

9.4.1 Experimental datasets

Finding experimental data on the cognitive reactions during the spread of messages in disaster situations is difficult. The data concerning the messages is mostly missing or protected by messenger services. The information about cognitive states of people in the context of message receiving is difficult to obtain, due to limitations on the extraction of the data. Therefore, we created two different experimental datasets based on our understanding of the problem and on the literature. Both datasets contain information about a person receiving a message about a disastrous situation that might occur.

The first experimental dataset defines the course of all 25 states for a person receiving a message through the telephone with a tensed emotion and negative sentiment. This person is easily influenced by the sentiment and emotion of the message and believes that the message is true. In figure 9.2 the course of the 25 states in the first dataset is shown. Bosse et al. [2] state that the emotion of a person is influenced by the impact of the emotion of another person and the person's own belief. We assume that the impact of the emotion is big, because this person received a telephone call and this person is easily influenced. It is considered that the person will react spreading the message.

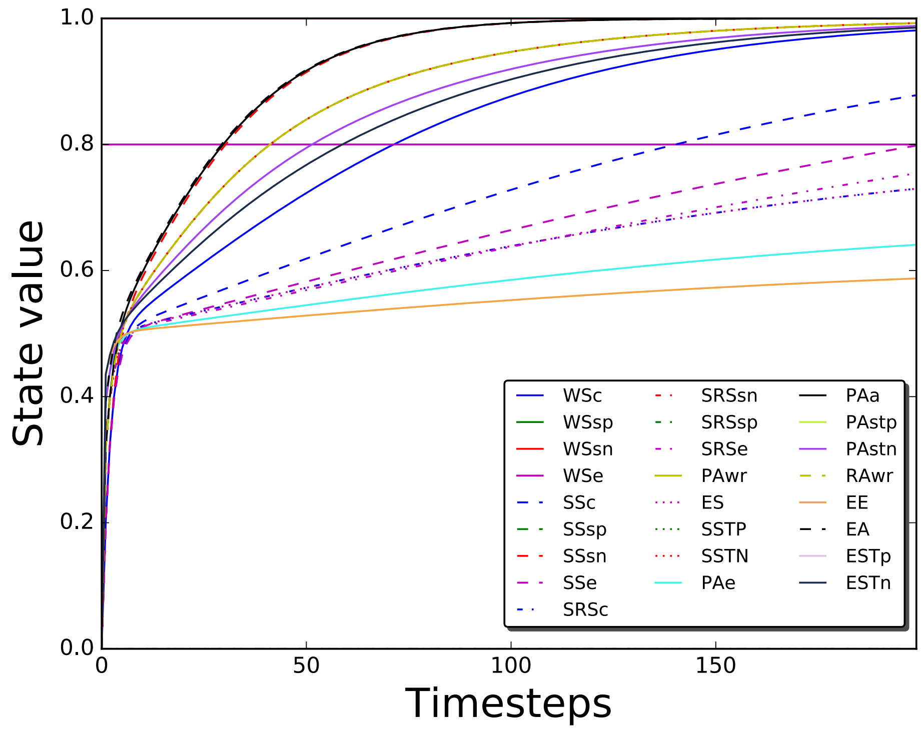

Fig. 9.2: Experimental dataset: Easily influenced person

The second experimental dataset defines the course of all 25 states for a person that receives a message through a messenger service. The observed emotion of the sender is happy and positive. This person is influenced by the emotion and sentiment of the message, however, believes that the message is not accurate enough to spread. In figure 9.3 the course of the second dataset is shown. It can be seen that this person's emotion and sentiment also approach the observed emotion and sentiment. The reason for this is that the person believes that the sender is happy and has a positive sentiment and is, therefore, influenced by the happy and positive sender. Because the value of the expected action is below 0.5 and this person believes that the message is not accurate enough, it is decided that this person will not revert to the action of spreading the message.

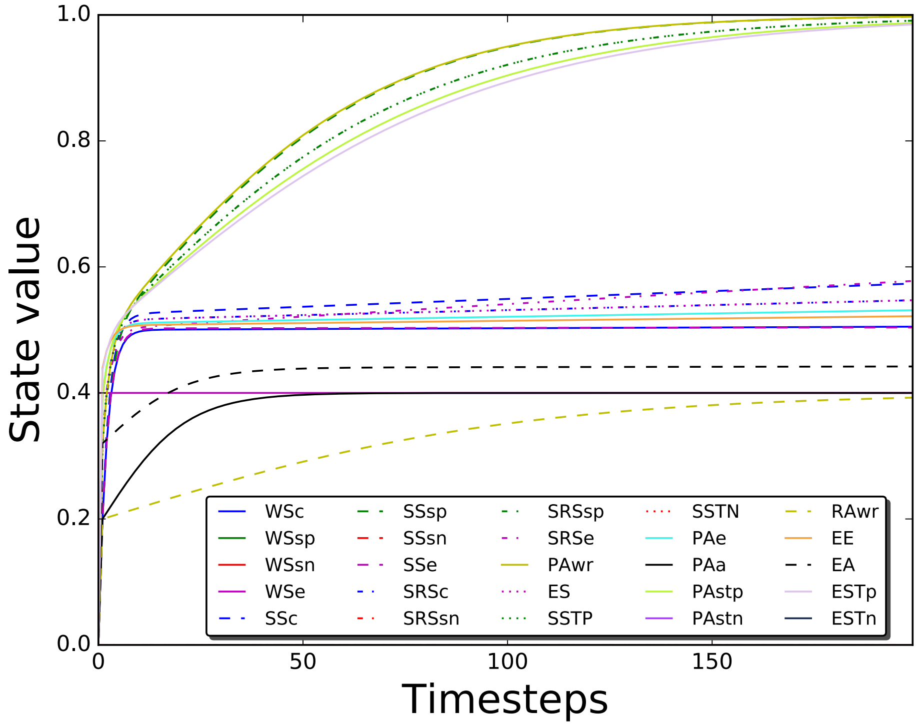

Fig. 9.3: Experimental dataset: Difficult to influence person

9.4.2 Parameter tuning methods

To tune the model, optimal values for the speed factor values η, the steepness σ and the threshold τ in the advanced logistic formulas should be found. For reasons of simplicity, we have decided to use a speed factor value of 0.4 for each state, because we assume that the changes of the states within a person to deal with receiving a disastrous message does not occur quickly, however, not too slowly either.

The steepness and threshold of the advanced logistic function is more difficult to manually define. In this model there are 14 states that use the advanced logistic function. Thus, in total there are 28 steepness and threshold values that need to be tuned. The domain of the steepness and threshold values is assumed to be $[-\inf, \inf]$.

This is another reason why manually tuning the parameters is difficult. We chose the mean squared error (MSE) as the objective function that has to be minimized.

We used random search to tune the parameters. To make parameter tuning with this method more tractable, we tuned 2 parameters instead of 28, and we searched within a uniformly distributed domain of $[-e^{-5}, e^{5}]$. This method provided errors of approximately 0.10 on the first dataset and of approximately 0.09 on the second dataset. When using the corresponding steepness and threshold values (see Table 9.2) in the model, this gave us an acceptable simulation.

Tab. 9.2: The resulting MSE, steepness and threshold after tuning.

	MSE	σ	τ
Dataset 1	0.103	5.859	-5.945
Dataset 2	0.094	0.847	-5.565

Tab. 9.3: Initial values of the input states of scenarios 1 and 2

Input states	Initial values scenario 1	Initial values scenario 2
WS_c	0.0	0.0
WS_{sp}	0.0	1.0
WS_{sn}	1.0	0.0
WS_e	0.8	0.4

Then, we performed random search with the modeling choice of tuning 28 parameters. This gave us an error of approximately 0.08, which is lower than tuning 2 parameters. However, when using the corresponding steepness and threshold values in the model, we got an abnormal simulation. We tried to decrease the domain to $[-e^{-2}, e^2]$. However, decreasing the domain did not make a difference.

9.5 Simulations and Results

In this section the simulation results are given. Three scenarios are simulated. For all simulations the steepness and threshold values from table 9.2 are used for each of the 14 states that use the advanced logistic function. We used a step size of $\Delta t = 0.1$ for all simulations, and the speed factor value η is 0.4.

The value of all connection weights are 1.0, except for the connection weights of $(SRS_c, SSTP)$, $(SRS_c, SSTN)$, $(PAwr, SSTP)$, $(PAwr, SSTN)$, (PA_a, PA_{stp}), (PA_a, PA_{stn}). The values of these weights are 0.01, because $\omega_{SRS_{sp} \to SSTP}$ and $\omega_{SRS_{sn} \to SSTN}$ should weigh the heaviest to calculate the state values of SSTN and SSTP.

9.5.1 Scenario 1: Receiving a tensed and negative phone call

In this first scenario, a person receives a phone call from another person informing then that a disastrous situation might occur. The person observes that the sentiment of the message is negative, and that the emotion of the message is tensed. This person is easily influenced by the sentiment and emotion of the message, also because he/she received a telephone call, which is assumed to be a credible source. This person, therefore, believes more easily that the message is true.

The initial values of the input states can be found in table 9.3. We have defined a tensed emotion to be 0.8 and a happy emotion to be 0.4. This is based on the valence and arousal model of Valenza et al. [10]. In figure 9.4 all states are depicted for this person. In figure 9.5 only the input and output states are depicted.

The output states EST_n, EA_a, EE_e and input state WS_c go up to around 0.9 due to the message's effect at the person. Since an action (i.e. spreading a message about a disastrous situation) increases awareness about the danger, the WS_c value increases.

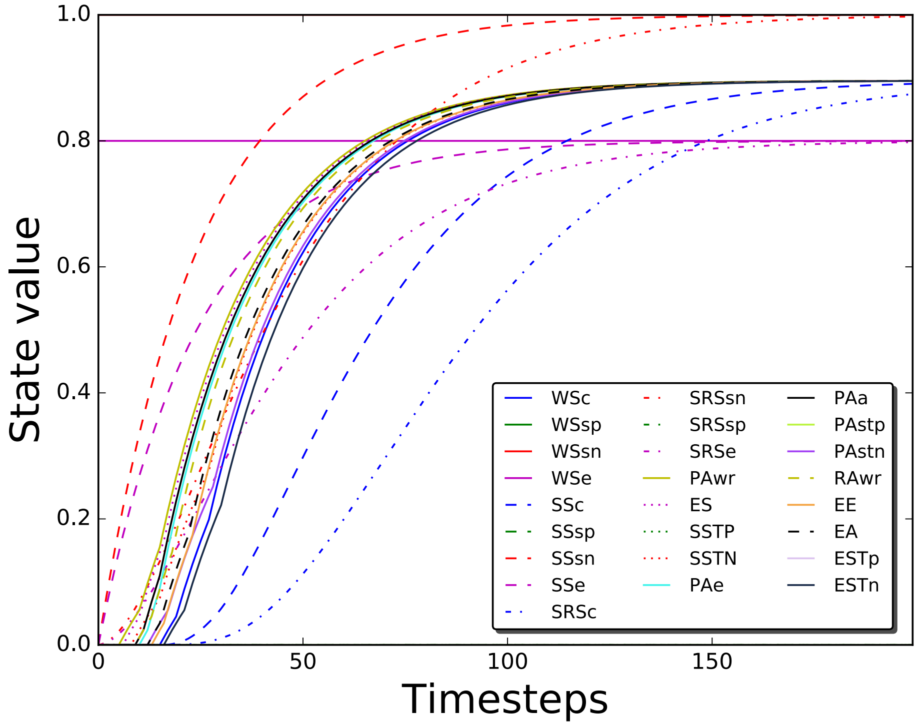

Fig. 9.4: Scenario 1: all states

9.5.2 Scenario 2: Receiving a happy and positive text message

In this scenario a person receives a message through a messenger service (textual) about a disastrous situation that might occur. This person, however, observes that the message has a positive sentiment and a happy emotion. This person is influenced by the message, however, does not believe that it is true enough to spread the message as it is more difficult to determine the sentiment and emotion of a textual message.

The initial values of the input states can be found in table 9.3. In figure 9.6 the simulation for this person is shown with all states. In figure 9.7 only the input and output states are shown for this person.

It can be seen that the EST_n is 0 over time, as the observed sentiment (WS_{sn}, WS_{sp}) of the message was positive. However, the EST_p state does not approximate to 1 throughout the simulation. This was expected since the connection weights that are important to define the EST_p are all 1.0. As expected, the E_e is higher than the WS_e, because this person observed a happy emotion and is influenced by it. The E_a is around 0.45. It is assumed that this person will not take action to spread the message, because this value is below 0.5.

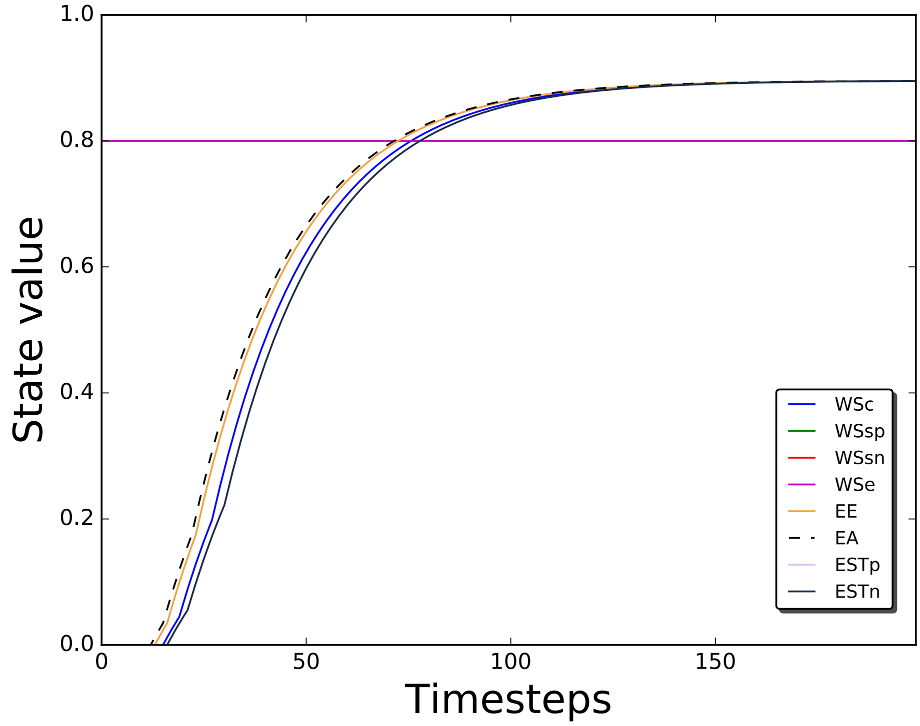

Fig. 9.5: Scenario 1: input and output states

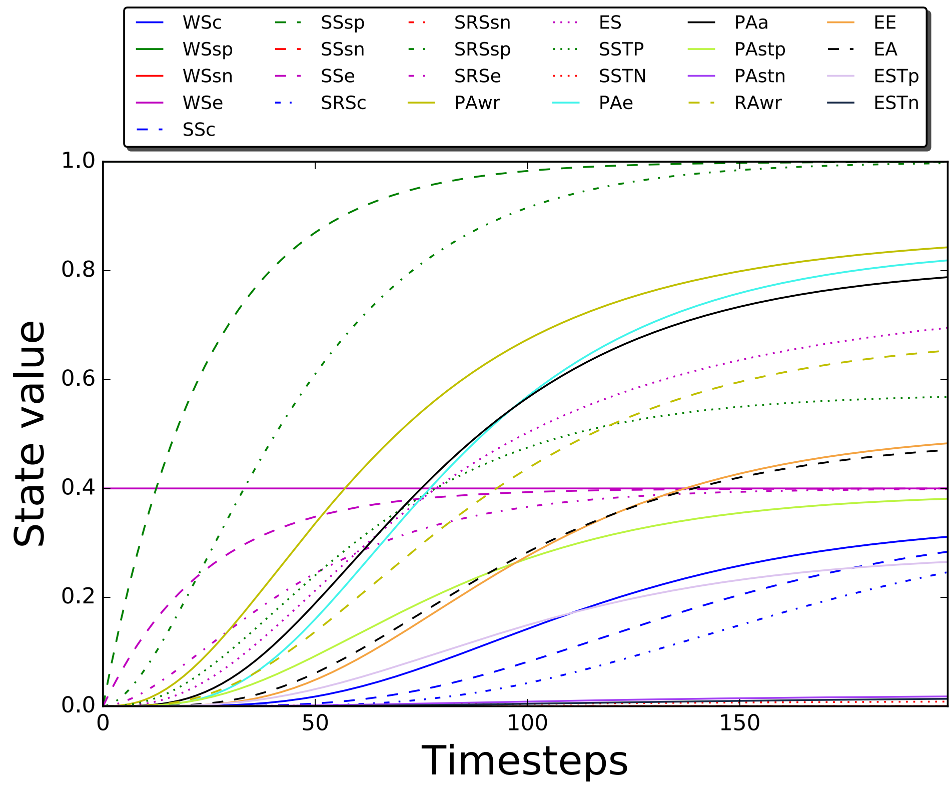

Fig. 9.6: Scenario 2: all states

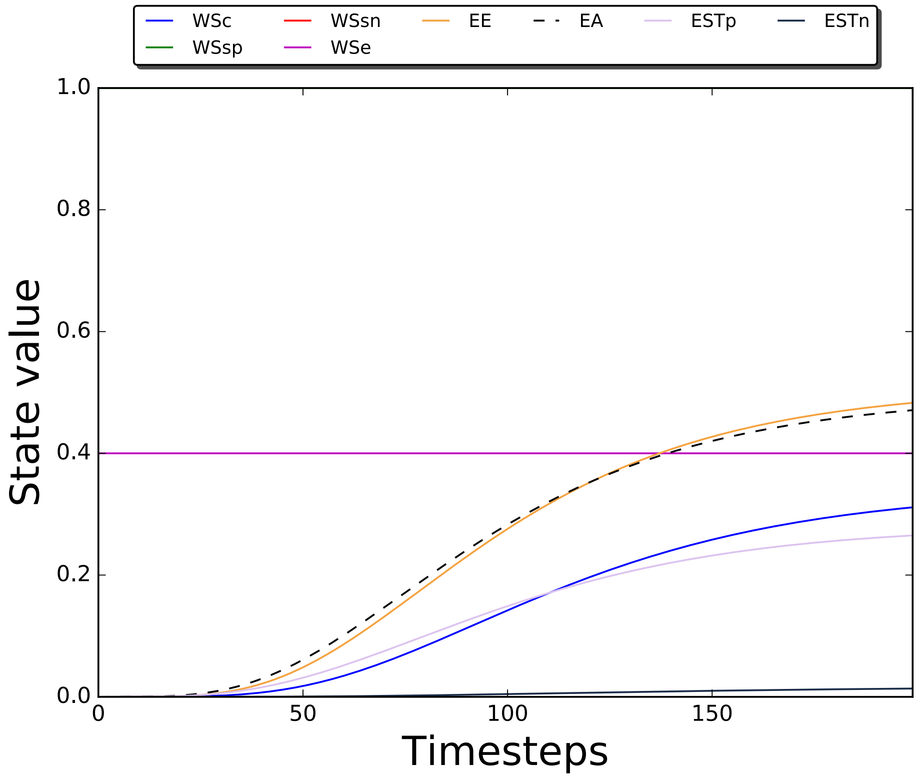

Fig. 9.7: Scenario 2: input and output states

9.5.3 Scenario 3: Outputs as inputs

In this scenario the person from scenario 1 receives a telephone call informing that a disaster might occur and takes action by sending a textual message to the person from scenario 2.

Tab. 9.4: Initial values of the input states of the two persons in scenario 3

Input states	Initial values person 1	Initial values person 2
WS_c	0.0	person1 E_a
WS_{sp}	0.0	person1 EST_{sp}
WS_{sn}	1.0	person1 EST_{sn}
WS_e	0.8	person1 E_e

The initial values can be found in table 9.4. In figure 9.8 the outputs of the first person and the outputs of the second person are shown. The outputs of the first person are used as inputs for the second person.

It can be seen that person 1 has a high EST_{sn}, and that person 2 also gets an EST_{sn} because of person 1. However, the EST_{sn} of person 2 is much lower than that of person 1. It is also shown that person 1 has a tensed emotion (i.e. $E_e = 0.8$), however, person 2 has a rather happy emotion (i.e. $E_e = 0.4$). It can, thus, be seen that person 2 is not influenced easily by the emotional state of person 1 as expected. The E_a of person 2 approximates a value of 0.4. Therefore, it is assumed that person 2 does not spread the message further.

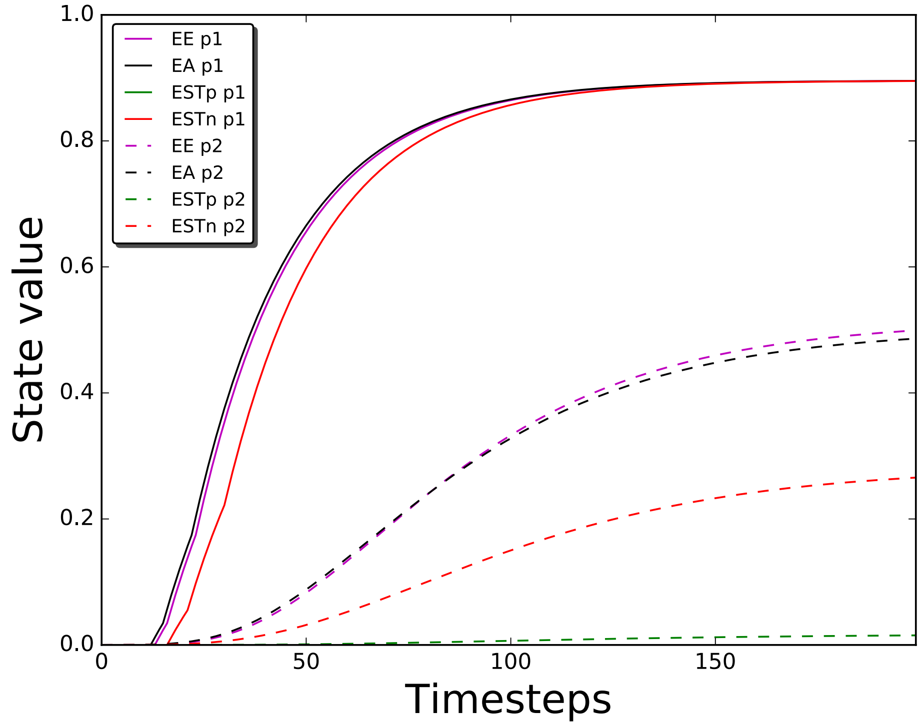

Fig. 9.8: Scenario 3: Outputs of person 1 as inputs for person 2

9.5.4 Mathematical analysis of the model

To determine when the model is in equilibrium, we check when the states reach their stationary points. For instance, a state Y has a stationary point if $\vec{d}Y(t)/\vec{d}(t) = 0$. The model is in equilibrium if every state has a stationary point at certain time t. Taking into account the difference and differential equations used in the model, the stationary point equation can be written as:

$$Y(t) = \vec{c}_Y(\omega_{X_1,Y}X_1(t), ..., \omega_{X_k,Y}X_k(t)) \tag{9.5}$$

As an example we are going to determine the stationary points for the states SS_c, SS_{sn}, and SS_e. The verification method is the substitution of values in the stationary point equations. To determine the stationary points, the person from the simulation in scenario 1 (figure 9.4) is used, however, with a longer simulation time and with a $\Delta t = 0.05$ (see figure 9.9).

The model was run until $Y(t + \Delta t) = Y$ holds. A stationary point for state SS_c was found at time point 531, with state value 0.8952. For state SS_e the stationary point is at time step 366 (state value of 0.7995). A stationary point for state SS_{sn} was found at time point 377 with state value 0.9995.

The connection states of SS_c, SS_e and SS_{sn} are respectively WS_c, WS_e and WS_{sn}. The state values of these connection states at the time points 531, 366 and 377

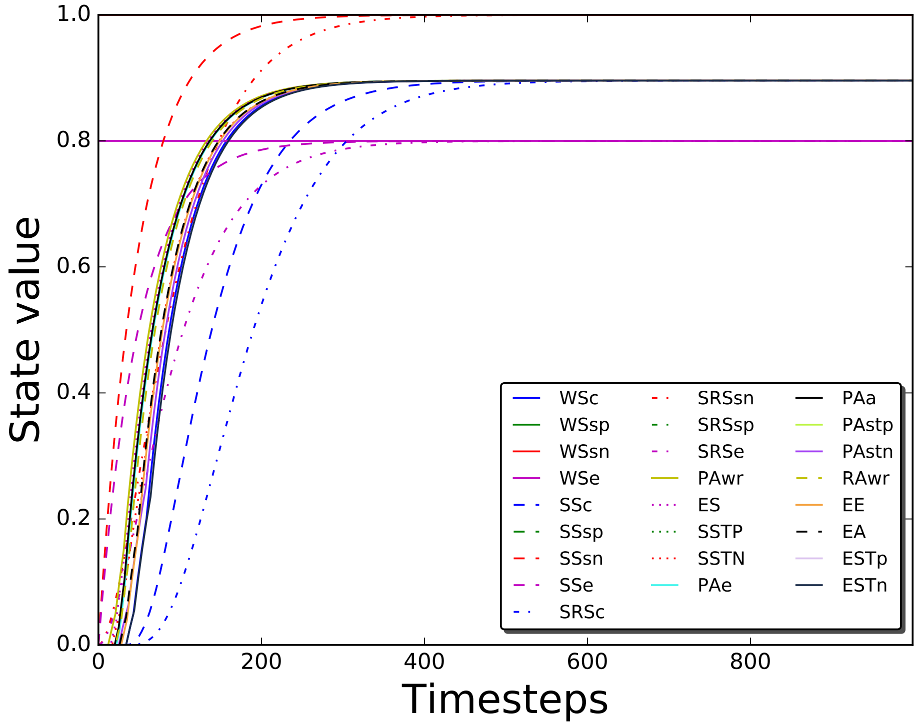

Fig. 9.9: Simulation for mathematical analysis

are, respectively, 0.8957, 0.8 and 1.0. The connection weights are are all 1.0. When substituting these values in equation 9.5 we can see that the equation holds with an accuracy of $< 10^{-2}$:

We found the stationary points for all states in the model. When taking into account that every state has to be stationary at time point t for the model to be in equilibrium, we can observe that the model is in equilibrium at time point 531 for the proposed set up.

9.6 Discussions and future works

In this paper a computational model is presented in order to model people's behaviour on spreading messages in disaster situations. The model was designed as a temporal causal network model, following the approach of Treur [9], moreover, inspired and based on findings from previous research, as discussed in the background information, section 2.

The proposed model can be a base for any type of disaster situation and can easily be extended in future research. Validation of this model is very difficult, if even possible, due to the lack of empirical data, because often observations during disaster situations are missing. Therefore, experimental data was created based on literature and experience to perform parameter tuning.

Within the scope of this paper we decided to incorporate different types of communication methods through the simulated scenarios. It could be interesting however to take those communication methods to the next level as well in order to learn why particular methods are more credible than others, or how messages spread more easily through some channels than others. Personality traits are somewhat incorporated in the simulation scenarios as well, however, for future research more traits should be explored. The same goes for culture and other possible influences.

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