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# To Help or Not to Help: A Network Modelling Approach to the Bystander Effect

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**Abstract.** This paper focuses on defining and simulating behavioural outcomes of the bystander effect. These insights were modeled by temporal-causal networks. Typical patterns of bystander behaviour were translated into three requirements and seven simulated scenarios of the bystander effect. All scenarios were simulated to showcase the main bystander effect dynamics and its accordance with the literature. Unknown parameters of the effect were further estimated by a Simulated Annealing algorithm. In the end, the created model shows the potential to simulate the bystander effect in different and new scenarios. The created model adhered to the stated three requirements and shows potential to verify the model predictions independently and for new bystander situations.

**Keywords:** Bystander effect · Network modelling · Simulated annealing

## 1 Introduction

Helping other people occurs more frequently when alone than in the company of passive bystanders [3]. This phenomenon is called the bystander effect, a prosocial behaviour affected by the altruistic nature of people; e.g., [10], p. 328. Here, help is defined as bystander intervention and occurs when a bystander offers support to the victim(s). This support is either expressed verbally and/or physically, in such that it affects the victim's cognitive or behavioural state over time. Cases with no help offered at all, are called bystander apathy. This was first investigated in the murder of Kitty Genovese [14], which was the main driver in literature to investigate why bystanders show these behavioural patterns [9, 14, 19].

With decades of subsequent research on the bystander effect topic (see Table 1 in Fischer et al. [8]), this study builds upon earlier research by combining causal relationships. Many relationships and patterns were found in the research of [8] but only focus on earlier research. By choosing some moderator variables from this research, the combined impact of moderator variables within (new) bystander situations can be determined. Within this paper, the following variables were chosen: Proportional Dominance Effect (PDE), In-Group Effect (IGE), Effect Evaluation (E), Dangerous emergency (DEm) and Distress (D) perception. These variables were firstly chosen due to its strong and unambiguous character within the bystander effect [1, 8]. Secondly, helping is often in line with the cost-reward model as the decision to act or not comes with benefits and drawbacks [7, 18]. With balancing variables in the cost-reward


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model, potential bystander intervention and apathy models are more likely to be simulated both.

As these five variables have an impact on the overall bystander effect, it is still necessary to define how the bystander effect works. Therefore, a conceptual model of Latané and Darley [15] is used as starting point for the bystander effect dynamics (see Fig. 1). While this model shows conceptually how bystanders make decisions, it does not clear where and how each moderator variables is incorporated. Also, with numerous other variables available, it is hard to pinpoint what the realistic combined total impact would be for every variable over time. Although, incorporating all found variables will result in a too large model that lacks focus. By using an initial solution that is in line with the cost-reward model, answers can still be found to gaps in the literature (e.g. unclarity what the in-between effects are between variables in [6]). The total combined impact of the five variables can be modeled within the temporal-causal networks by combination functions. With this in mind, simulating the effects between the five variables can be realised. The final goal of this paper is to determine what settings of the network characteristics simulate the bystander effect most realistically.

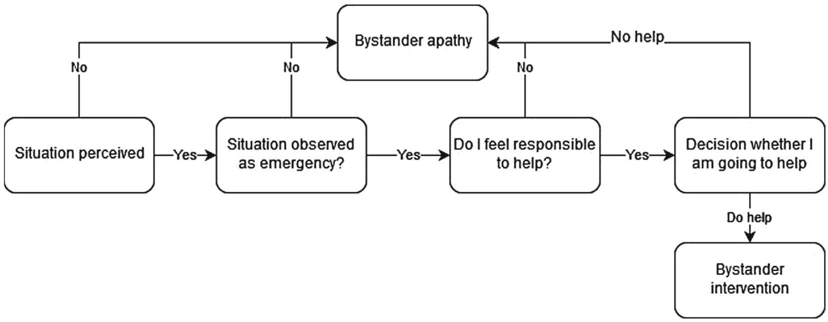


**Fig. 1.** Procedure for determining whether to help or not to help

## 2 The Network-Oriented Modelling Approach

First, the Network-Oriented Modelling approach is explained in some detail. The approach was described in [20] and addresses how mental and behavioural states change over time. For each state, characteristics are given to calculate the state value over time, which leads to the opportunity of model complex processes in an easy, structured and intuitive manner. This approach allows to incorporate temporal complexity into causal graphs. In total, three network structure characteristics are used for a model; together they define a temporal-causal network model:

- **Connectivity:** connection weights $\boldsymbol{\omega}_{X,Y}$ from a state $X$ to a state $Y$
- **Aggregation:** a combination function for each state $Y$, denoted by $\mathbf{c}_Y(..)$
- **Timing:** a speed factor for each state $Y$, denoted by $\boldsymbol{\eta}_Y$

This is a model where the connections between states and other network characteristics are defined in a declarative mathematical manner. By the developed dedicated modeling environment (see [21], Chap. 9), the mentioned network characteristics are transformed automatically into a numerical representation that can be used for simulation, which has the definitions shown in Table 1.

**Table 1.** Numerical representations for a temporal-causal network model

| Concept | Representation | Explanation |
|---|---|---|
| State values over time $t$ | $Y(t)$ | At each time point $t$ each state $Y$ in the model has a real number value in [0, 1] |
| Single causal impact | $\mathbf{impact}_{X,Y}(t) = \boldsymbol{\omega}_{X,Y}\, X(t)$ | At $t$ state $X$ with connection to state $Y$ has an impact on $Y$, using connection weight $\boldsymbol{\omega}_{X,Y}$ |
| Aggregating multiple impacts | $\mathbf{aggimpact}_Y(t)$ $= \mathbf{c}_Y(\mathbf{impact}_{X1,Y}(t), \ldots, \mathbf{impact}_{Xk,Y}(t))$ $= \mathbf{c}_Y(\boldsymbol{\omega}_{X1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{Xk,Y}X_k(t))$ | The aggregated causal impact of multiple states $X_i$ on $Y$ at $t$, is determined using a combination function $\mathbf{c}_Y(V_1, \ldots, V_k)$ and applying it to the $k$ single causal impacts |
| Timing of the causal effect | $Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y\, [\mathbf{aggimpact}_Y(t) - Y(t)]\, \Delta t = Y(t) + \boldsymbol{\eta}_Y\, [\mathbf{c}_Y(\boldsymbol{\omega}_{X1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{Xk,Y}X_k(t)) - Y(t)]\, \Delta t$ | The causal impact on $Y$ is exerted over time gradually, using speed factor $\boldsymbol{\eta}_Y$; here the $X_i$ are all states from which state $Y$ has incoming connections |

## 3 The Introduced Temporal-Causal Network Model

In Fig. 1 an overview of the model for the bystander effect is shown. In total, four areas were identified. For each area, an in-depth literature analysis was conducted to find which variables belong to which area and/or which states $X_k$ can be defined. Starting with a situation where a potential bystander effect could first occur, is the perception of the event. When an event is not perceived, the individual will not intervene at all. This perception is dependent upon the individual sensory capabilities; e.g., [20], p. 213. In this model, various variables were perceived from the world, processed and interpreted by the sensory system, and given meaning to. The meaning is determined by making a trade-off of all input variables and decide to act upon or not. This process is highly similar to Fig. 1, where conceptually it is shown how the bystander effect works. Next, the position of found states $X_k$ require to be defined. In total, five variables were defined which are all handled as a chain of states within a person. This chain means that each variable has its perception of the world, the collection and interpretation of the sensory input, leading to a certain meaning and belief to it. This chain starts with specified values from the given variables, which are the costs and rewards. The following three variables were identified: Identifiable Victim Effect (IVE), In Group Effect (IGE), and the Propositional Dominance Effect (PDE) [5, 6, 13]. With clear effects in the latter two, Fischer et al. [8] argue that the effect of helping someone familiar is not different from an unknown person. Therefore, IVE remains unambiguous as a variable input variable. With this information, PDE and IGE remain within the scope of the research and more clarity is needed on the IVE aspect. For PDE, Erlandsson et al. [6] state:

> 'First, a within-subject contrast test showed that there was a linear trend on helping motivation, $F(1,38) = 55.67$, $p < 0.001$, $\eta^2 = 0.594$. As predicted, helping motivation increased as the victim reference-group got smaller.' (p. 5).

For IGE, the following is stated in the same paper:

> 'First, a within-subject contrast test showed that there was a linear trend on helping motivation, $F(1,38) = 105.58$, $p < 0.001$, $\eta^2 = 0.735$. As predicted, helping motivation increased as the victim became more part of one's in-group' (p. 6).

This shows that PDE and IGE are both strong determinants with IGE having a larger effect. In both a cost and rewarding perspective, Dangerous Emergencies (DEm) play a role in either one perspective dependent on how dangerous the situation becomes. Fischer et al. [7] show that dangerous situations are perceived better and lead to intervening more often than in non-dangerous situations. Therefore, when the emergency need is low, one will show apathy more frequently (which is depicted in Fig. 1 as well in step two). Also, the need to help will increase over time when the situation becomes more dangerous. In the paper of Fischer et al. [8], it is stated:

> 'In the present meta-analysis, perceived danger is reflected by the following coded variables: (a) emergency danger (high vs. low), (b) perpetrator present versus absent (…) As expected, non-emergencies ($g = -0.47$, $SE = 0.041$, $Z = -11.42$, $p < 0.001$, $N = 22$) yielded a larger bystander effect than dangerous emergencies ($g = -0.30$, $SE = 0.048$, $Z = -6.34$, $p < 0.001$, $N = 65$) and potentially dangerous villain acts ($g = 0.29$, $SE = 0.101$, $Z = 2.82$, $p < 0.005$, $N = 14$)' (p. 7).

Therefore, a key influence to the DEm is the presence of a fierce perpetrator [8]. With no fierce perpetrator present, bystander apathy will more likely occur and intervention when that person is present. From a cost perspective only, Distress (D) is added as it affects the bystander effect [2]. When the distress level is enhanced, an avoidance or freezing dominated bystander apathy effect occurs [12]. Furthermore, in this paper is stated that 'only personal distress predicted the negative effect of bystanders during an emergency.' (p. 252). Determining the costs and rewards is explained by the other states in the model. An individual evaluates (E) the situation all the input and prepares an answer to the situation. For example, Fischer et al. [7] state:

> 'Dangerous emergencies should be associated with a clearer and earlier recognition of the emergency, resulting in an increased degree of empathic arousal, increased attribution of personal responsibility, and thus a greater willingness to accept increased costs for helping.' (p. 270).

This means that the costs and rewards are weighed. Dovidio, Piliavin, Gaertner, Schroeder, and Clark III [4] show that when the costs of helping are low, people will more likely intervene when the net costs are high. The outcomes do not outweigh the potential rewards from it, where the Effect Evaluation (E) plays a decisive role. This intervention has a specific effect on the overall variables and whether it is smart to help in a certain situation. All insights lead to Fig. 2, which show a temporal-causal model for the bystander effect. In this case, only one individual is shown and determined for whether they will show bystander apathy or intervention. All abbreviations mentioned in Fig. 2 are explained in a Table 2. Summarized, this network model contains state variables (called states) starting with a world state $ws_x$ that affects the sensory state $ss_x$ for a stimulus x. This leads to a sensory representation state $srs_x$ and a certain belief $b_x$ of the bystander situation. Based on literature, other states have been added. The belief of all discussed states influence the balance between positive influence $p_{inf}$ and negative influence $n_{inf}$. Next, a decision is prepared as $ps_a$ and finally the actual action execution is performed, modeled as $es_a$.

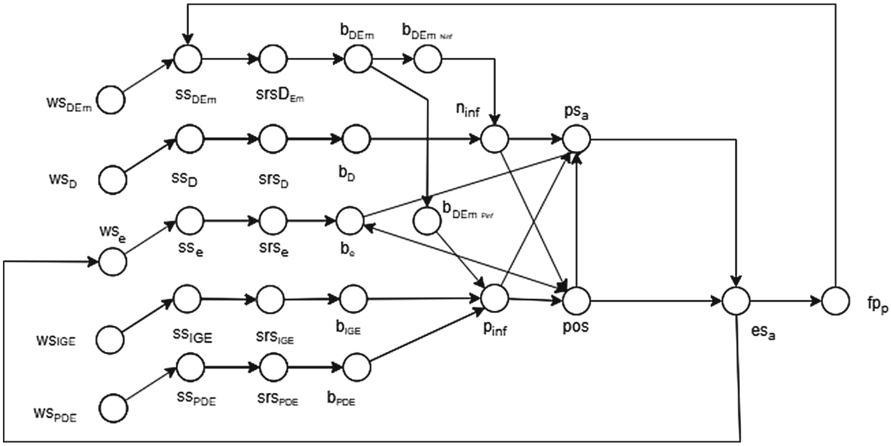


**Fig. 2.** Connectivity of the temporal-causal network for an individual determining to help a victim. The states and causal connections provide an overview of the factors that play a role in the causation for the decision to help or not to help.

**Table 2.** Explanation of the states

| State Nr | Name | Explanation |
|---|---|---|
| $X_{1\text{-}5}$ | $ws_x$ | World state for stimulus *x* |
| $X_{6\text{-}10}$ | $ss_x$ | Sensor state for stimulus *x* |
| $X_6$ | $ss_D$ | Sensor state for stimulus Distress (D) |
| $X_7$ | $ss_{DEm}$ | Sensor state for stimulus Dangerous Emergency (DEm) |
| $X_8$ | $ss_{IGE}$ | Sensor state for stimulus In-Group Effect (IGE) |
| $X_9$ | $ss_{PDE}$ | Sensor state for stimulus Proportional Dominance Effect (PDE) |
| $X_{10}$ | $ss_e$ | Sensor state for effect e |
| $X_{11\text{-}15}$ | $srs_x$ | Sensory representation state for *x* |
| $X_{16\text{-}22}$ | $b_x$ | Interpretation of sensory representation for *x* |
| $X_{21}$ | $b_{DEmpinf}$ | Belief state for rewarding influence of a dangerous emergency situation |
| $X_{22}$ | $b_{DEmninf}$ | Belief state for cost influence of a dangerous emergency situation |
| $X_{23}$ | $n_{inf}$ | Interpretation of costs of incoming variables |
| $X_{24}$ | $p_{inf}$ | Interpretation of rewards of incoming variables |
| $X_{25}$ | pos | Prior ownership state for action a with incoming belief $b_e$ |
| $X_{26}$ | $ps_a$ | Preparation state for response action a |
| $X_{27}$ | $es_a$ | Execution state for action a |
| $X_{28}$ | $fp_p$ | Presence of a fierce perpetrator |

## 4 Simulation Results

In order to determine the quality of the simulation, several patterns were found in the previous section. These were written in the form of model requirements to show which outcomes the bystander effect:

1. An increasing dangerous emergency situation will positively influence the bystander intervention [8].
2. When a person has a strong IGE/PDE, the bystander will intervene in both situations but IGE will be faster than PDE [6].
3. When the costs overpowers the rewards, the probability of helping will decrease (and increase when vice versa) [4].

All the given requirements were divided in seven scenarios to showcase the patterns. For the first requirement, three scenarios are used to show how the likelihood of intervening will increase with a higher danger perception. For this, three different parameters were used to depict a dangerous emergency situation: low danger (0.2), medium danger (0.5) and high danger (0.8). Each initial value is always chosen within the scale of [0,1], using 0.5 as the person's relative perception as what an average danger is. The simulations are shown in Fig. 3. Here, as in the other graphs, time is on the horizontal axis and activation level on the vertical axis. According to earlier found research, there should be an increase in bystander intervention when the situation becomes more dangerous until tipping point T. This tipping point leads to an individual showing bystander intervention and not apathy anymore. In Fig. 3, the three respective scenarios are depicted with an additional letter A for the intervention.

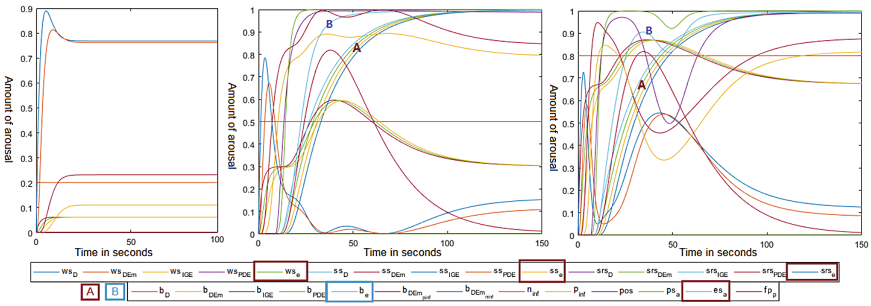


**Fig. 3.** Three different scenarios with DEm = 0.2 (left), DEm = 0.5 (middle), DEm = 0.8 (right). Here A indicates the intervention.

This letter shows four lines (depicted as A) that show the pattern of bystander intervention as it slowly converges to value 1 in the latter two graphs. Generally, when the belief $b_e$ of the effect e is high, one will act in the situation (line depicted with B). These lines are the most interesting of all depicted variables: they depict a positive effect evaluation and thus a higher possibility of acting represented by $es_a$. In the dangerous situation of DEm = 0.2, no intervention is depicted as the individual will show bystander apathy. In the middle graph, the faster intervention takes place as the situation is more dangerous than the left one, which is according to the found pattern. Interestingly, DEm = 0.8 does not yield a much faster intervention than DEm = 0.5. This is most likely due to the higher costs of helping. For the second requirement, the descriptive statistics in the research of Berggren et al. [1] were used. Both IGE and PDE variables have an bystander intervention pattern when either one or both of the values are high. The expected pattern would be that PDE leads to a faster intervention due to $\eta^2 = 0.735$ than the score of IGE with $\eta^2 = 0.594$.

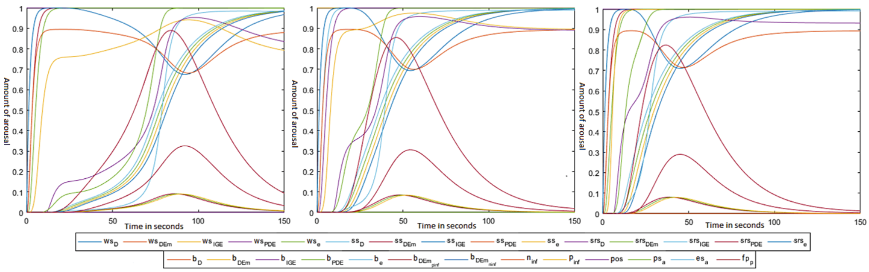


**Fig. 4.** Simulations of different PDE/IGE values with left PDE = 0 and IGE = 1, in the middle PDE = 1 and IGE = 0, and right both value one. As shown the bystander intervention occurs faster from right to left.

In Fig. 4, three scenarios are given with PDE = 0 and IGE = 1, PDE = 1 and IGE = 0, and both variables with value one. In the last requirement, negative influences should overpower the positive ones. A clear case to depict this, is a very distressed situation (D = 1). This simulation is shown in Fig. 5.

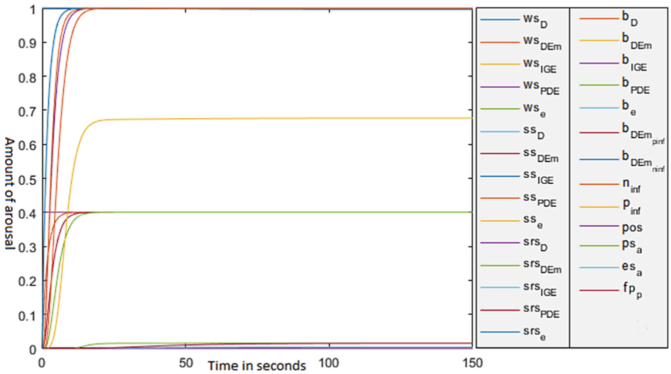


**Fig. 5.** Simulations of a very distressed, dangerous emergency situation. The state of $Es_a$ reaches at highest a value of 0.02.

In the figure, no intervention and almost no dynamics are found in this graph. The costs of the situation are too high, leading to no action at all. The scenario where primarily positive outcomes do not require to be modelled again, as various examples were given in Fig. 4 already.

## 5 Mathematical Verification of the Network Model

Based on the differential equation in Table 1, stationary points or equilibria of the created model can be verified by calculating for states $X_i$ in which $dX_i/dt = 0$ the **aggimpact**$_{X_i}(t)$ for $X_i$ and comparing the deviation of this to the simulation outcome $X_i(t)$; see Table 3. For this verification, the last graph of Fig. 3 (DEm = 0.8) was used to calculate the mathematical validity of the model. For the chosen graph, the intervention degree is almost in an equilibrium at time step $t = 150$. By doubling this amount to $t = 300$, it is assured that the equilibrium is certainly approximated. The following procedure described in [20], p. 327, is used for the mathematical verification:

**Table 3.** Mathematical verification of the created bystander effect model, based on the metrics of the last graph of Fig. 3 at time point $t = 300$.

| State $X_i$ | State name | $X_i(t)$ | aggimpact$_{X_i}(t)$ | Deviation |
|---|---|---|---|---|
| $X_1$ | $ws_D$ | 0 | 0 | 0 |
| $X_2$ | $ws_{DEm}$ | 0.8000 | 0.8000 | 0 |
| X3 | $ws_{IGE}$ | 0 | 0 | 0 |
| $X_4$ | $ws_{PDE}$ | 0 | 0 | 0 |
| $X_5$ | $ws_e$ | 0.9990 | 0.9990 | $5.16 * 10^{-8}$ |
| $X_6$ | $ss_D$ | 0 | 0 | 0 |
| $X_7$ | $ss_{DEm}$ | 0.6734 | 0.6734 | $-1.33 * 10^{-7}$ |
| $X_8$ | $ss_{IGE}$ | 0 | 0 | 0 |

(*continued*)

**Table 3.** (*continued*)

| State $X_i$ | State name | $X_i(t)$ | aggimpact$_{Xi}(t)$ | Deviation |
|---|---|---|---|---|
| $X_9$ | $ss_{PDE}$ | 0 | 0 | 0 |
| $X_{10}$ | $ss_e$ | 0.9990 | 0.9990 | $5.72812 * 10^{-8}$ |
| $X_{11}$ | $srs_D$ | 0 | 0 | 0 |
| $X_{12}$ | $srs_{DEm}$ | 0.6734 | 0.6734 | $-1.482 * 10^{-7}$ |
| $X_{13}$ | $srs_{IGE}$ | 0 | 0 | 0 |
| $X_{14}$ | $srs_{PDE}$ | 0 | 0 | 0 |
| $X_{15}$ | $srs_e$ | 0.9990 | 0.9990 | $6.36 * 10^{-8}$ |
| $X_{16}$ | $b_D$ | 0 | 0 | 0 |
| $X_{17}$ | $b_{DEm}$ | 0.6734 | 0.6734 | $-1.65 * 10^{-7}$ |
| $X_{18}$ | $b_{IGE}$ | 0 | 0 | 0 |
| $X_{19}$ | $b_{PDE}$ | 0 | 0 | 0 |
| $X_{20}$ | $b_e$ | 0.9929 | 0.9933 | 0.0038 |
| $X_{21}$ | $b_{DEmpinf}$ | 0.8798 | 0.8798 | $2.54 * 10^{-7}$ |
| $X_{22}$ | $b_{DEmninf}$ | 0.1202 | 0.1202 | $-2.54 * 10^{-7}$ |
| $X_{23}$ | $n_{inf}$ | 0.0820 | 0.0820 | $-2.24 * 10^{-7}$ |
| $X_{24}$ | $p_{inf}$ | 0.8205 | 0.8205 | $2.101 * 10^{-7}$ |
| $X_{25}$ | pos | 0.98999 | 0.99248 | 0.0025 |
| $X_{26}$ | $ps_a$ | 0.99991 | 0.99997 | $6.35 * 10^{-5}$ |
| $X_{27}$ | $es_a$ | 0.99899 | 0.99904 | $4.994 * 10^{-5}$ |
| $X_{28}$ | $fp_p$ | 0.004 | 0.004 | $-1.85 * 10^{-6}$ |

1. The simulation is generated of DEm = 0.8.
2. For a number of states $Y$ identify stationary points with their time points $t$ and state values $Y(t)$.
3. For each of these stationary points for a state $Y$ at time $t$ identify the values $X_1(t), .., X_k(t)$ at that time of the states $X_1, .., X_k$ connected toward $Y$.
4. Substitute all these values $Y(t)$ and $X_1(t), .., X_k(t)$ in the criterion $\mathbf{c}_Y(\boldsymbol{\omega}_{X1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{Xk,Y}X_k(t)) = Y(t)$ derived from Table 1.
5. If the equation holds (for example, with an accuracy $<10^{-2}$), then this test succeeds, otherwise it fails.
6. If this test fails, then it has to be explored were the error can be found.

The outcomes are provided in Table 3. As shown, the accuracy of each state is very high with a deviation rate of $<10^{-3}$. Therefore, the model shows evidence that it is mathematically valid.

## 6 Validation Using Empirical Data and Parameter Tuning

In the simulation results section, three requirements with seven simulations were already depicted. While this output shows interesting insights, many different scenarios and other dependencies remain untested. The requirements were already based on literature and clear effects were found between several moderating variables. However, the requirements on itself could lead to a certain clash, which is still interesting to further investigate. For example, on the one hand the first requirement is stated that an increasing dangerous emergency will lead to more bystander intervention. On the other hand, the third requirement states that costs will overpower the rewards, the probability of helping will decrease. In situations where emergencies become more than highly dangerous (DEm = [0.83,1]), investigating this further will further tune the overall model. Outcomes of such models are depicted in Fig. 6.

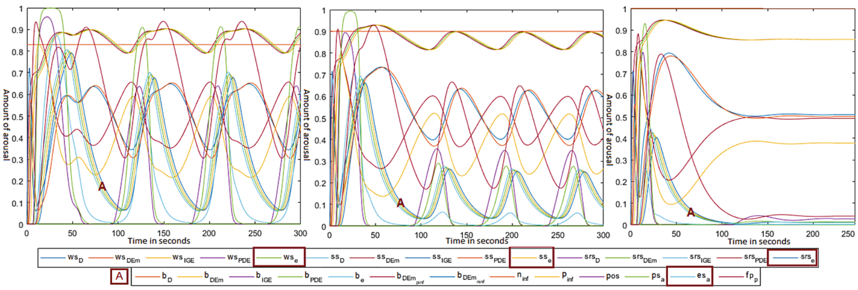


**Fig. 6.** Three different scenarios with DEm = 0.83 (left), DEm = 0.9 (middle), DEm = 1.0 (right). Here A depicts the intervening.

In these three new scenarios, it is shown that primarily requirement three is still true. The costs outweigh the rewards and thus the amount of rewards and intervening (A) slowly becomes less likely. This brings two possible outcomes, which are either:

1) Requirement one remains true at all times, thus a very dangerous situation of DEm = 1, never outweighs the costs, or
2) Requirement two remains true, thus the rewards are outweighed by the costs.

Both scenarios are tested with an algorithm called Simulated Annealing, which tries to find what the most probable answer would be and which parameters come along. For this, the middle scenario of DEm = 0.9 is chosen due to being a very dangerous situation but remains an average very dangerous one. In total N = 14000 iterations with the algorithm were performed, consisting of four runs of n = 3500. The parameter tuning was executed by using the initial values of the states $X_{23}$–$X_{27}$. These values were determined until the first possible execution in state $X_{27}$, in such that the final decision can be determined by the algorithm (see line B in Fig. 7). The chosen network characteristics were tuned in multiple ways: the threshold $\boldsymbol{\tau}$ and speed values $\boldsymbol{\eta}$ of states were tuned in all runs. Also, two different approaches were chosen, which were the tuning of the connection weights $\boldsymbol{\omega}_{X,Y}$:

1) Only tuning the connection weights to state $X_{27}$ ($es_a$), which led to 12 characteristics being tuned, and
2) In addition tuning all connection weights that start as incoming connection from $X_{23}$ till $X_{27}$.

This led to 16 characteristics being tuned. In Table 4 below, the results are shown in terms of optimal values per scenario and what the root mean square error (RMSE) is. This showcases an estimate of how the SA algorithm worked.

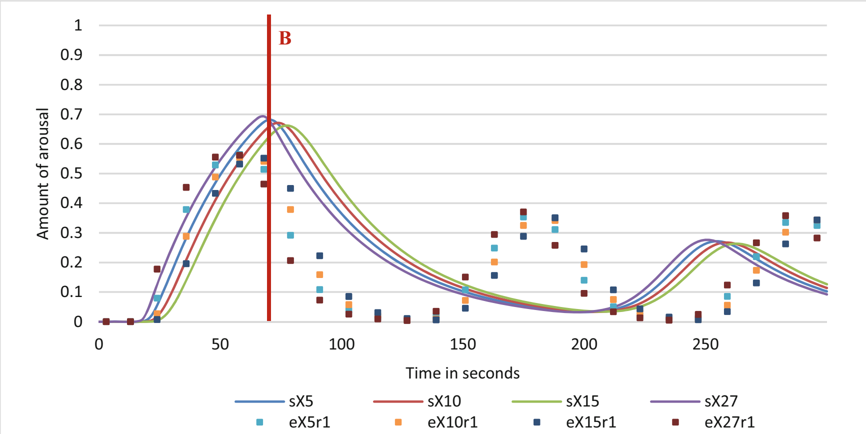


**Fig. 7.** RMSE errors over time for Run 1 in Table 3 with best scoring RMSE = 0.096

In Fig. 7, it is clear that requirement 3 overpowers the first requirement. The costs are higher than the rewards, thus based on these parameters, the outcome would require the first requirement to be adjusted: ‘An increasing dangerous emergency will positively influence the bystander intervention until tipping point T has reached. When this point is reached, there is an increasing possibility of bystander apathy’. Finally, the other runs in Table 4 were taken into account as well. It shows that run 3 (r3) and 4 (r4) contradict the new requirement by stating requirement one remains true (see Fig. 8). Further research is needed to state what happens when the situation is very dangerous. When this is clear, the set of parameters can be used in Table 4.

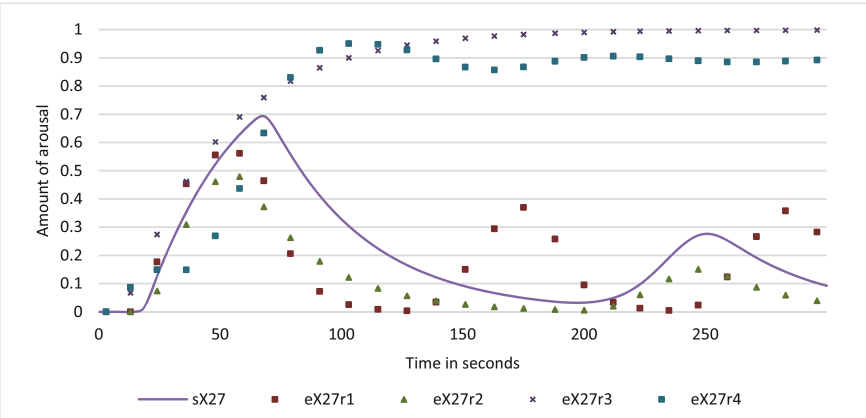


**Fig. 8.** Deviations over time for Run 1 in Table 3 with best scoring RMSE = 0.096

**Table 4.** RMSE and outcomes of the SA-algorithm

| Run | Speed factors η | Thresholds τ | Connection weights ω | RMSE |
|---|---|---|---|---|
| Run 1 - 12 characteristics (i = 3500) | $n_{inf}$ = 0.715<br>$p_{inf}$ = 0.23<br>pos = 0.9659<br>$ps_a$ = 0.689<br>$es_a$ = 0.168 | $n_{inf}$ = 0.297<br>$p_{inf}$ = 0.10<br>pos = 0.23<br>$ps_a$ = 0.47<br>$es_a$ = 0.24 | $\omega_{pos,esa}$ = 0.82<br>$\omega_{psa,esa}$ = 0.174 | 0.096326 |
| Run 2 - 12 characteristics (i = 3500) | $n_{inf}$ = 0.134<br>$p_{inf}$ = 0.272<br>pos = 0.55<br>$ps_a$ = 0.511<br>$es_a$ = 0.063 | $n_{inf}$ = 0.446<br>$p_{inf}$ = 0.916<br>pos = 0.10<br>$ps_a$ = 0.6214<br>$es_a$ = 0.0003 | $\omega_{pos,esa}$ = 0.79<br>$\omega_{psa,esa}$ = 0.09 | 0.108578 |
| Run 3 - 19 characteristics (i = 3500) | $n_{inf}$ = 0.743<br>$p_{inf}$ = 0.84<br>pos = 0.999<br>$ps_a$ = 0.145<br>$es_a$ = 0.05 | $n_{inf}$ = 0.407<br>$p_{inf}$ = 0.693<br>pos = 0.554<br>$ps_a$ = 0.076<br>$es_a$ = 0.409 | $\omega_{be,\ pos}$ = 0.599<br>$\omega_{be,\ psa}$ = 0.599<br>$\omega_{ninf,\ pos}$ = 0.603<br>$\omega_{ninf,\ psa}$ = 0.603<br>$\omega_{pinf,\ pos}$ = 0.904<br>$\omega_{ninf,\ psa}$ = 0.904<br>$\omega_{pos,\ psa}$ = 0.033<br>$\omega_{pos,\ esa}$ = 0.911<br>$\omega_{psa,\ esa}$ = 0.913 | 0.132568 |
| Run 4 - 19 characteristics (i = 3500) | | $n_{inf}$ = 0.44<br>$p_{inf}$ = 0.711<br>pos = 0.076<br>$ps_a$ = 0.756<br>$es_a$ = 0.734 | $\omega_{be,\ pos}$ = 0.134<br>$\omega_{be,\ psa}$ = 0.134<br>$\omega_{ninf,\ pos}$ = 0.71<br>$\omega_{ninf,\ psa}$ = 0.71<br>$\omega_{pinf,\ pos}$ = 0.1624<br>$\omega_{ninf,\ psa}$ = 0.1624<br>$\omega_{pos,\ psa}$ = 0.494<br>$\omega_{pos,\ esa}$ = 0.827<br>$\omega_{psa,\ esa}$ = 0.8317 | 0.155321 |

## 7 Discussion

The review of the literature led to insights into behaviour patterns. By transforming these patterns into requirements, simulations were performed to test certain outcomes of the bystander effect. In total, ten scenarios were tested and gave insights into several expected patterns. The outcomes are following the empirical literature, which provides a possibility to model more complicated patterns. By checking the mathematical validity of the model, it is proven that the outcomes of the simulation are correct. Next, the dependency of variables was checked by using the SA algorithm and simulating N = 14000 cases. It was shown that the best scoring run, led to a refinement in the first requirement. The created model adhered to the three identified requirements and shows potential to verify the model predictions independently and for new bystander situations.

Certain limitations in the work require more attention. In terms of the temporal-causal model itself, the bystander effect is largely affected by other moderating non-depicted variables as well. This provides a potential to incorporate these, such as group size [3, 8, 16, 17], competency of bystanders [8], harm avoidance [11], and the further investigation of IVE [1, 8]. Another interesting issue is the investigation of weak connection weights between states. In Table 2, only relatively stronger relations are shown, while multiple small impacts could alter the overall outcome. Such weak connection weights could also be expressed in the way different individuals communicate with each other. Now, only one bystander is simulated while in real-life situations, multiple people are present. This leads to a certain shared responsibility, as shown in Fig. 1. By defining the impact of different bystanders, more complex insights can be modelled. Another way is to give more characteristics to the fierce perpetrator or the victim as these are not within the focus of this paper. Lastly, the paper had a focus on real-life situations while the bystander effect could occur online as well. Investigating this in an online setting has an easier empirical data collection possibility than in real life.

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