

A Self-Modeling Network Model Addressing Controlled Adaptive Mental Models for Analysis and Support Processes

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In this paper, a self-modeling mental network model is presented for cognitive analysis and support processes for a human. These cognitive analysis and support processes are modeled by internal mental models. At the base level, the model is able to perform the analysis and support processes based on these internal mental models. To obtain adaptation of these internal mental models, a first-order self-model is included in the network model. In addition, to obtain control of this adaptation, a second-order self-model is included. This makes the network model a second-order self-modeling network model. The adaptive network model is illustrated for a number of realistic scenarios for a supported car driver.

1. Introduction

To describe complex cognitive processes, including their formation, learning, development or adaptation, often the concept of (internal) mental model is used; for example, [1–4]. The focus here is on monitoring and assessing the performance of a human in demanding circumstances and generating support actions whenever needed. As an example, when we observe that a driver is consuming alcohol, the assessment will be that it will not be safe to start driving. Based on that, as a support action, starting the car will be blocked. Or if while driving it is observed that the driver's steering is erratic, this will be assessed as a driving risk. Therefore as a support action in this case, it will be proposed to slow down the car.

In such analysis and support processes, two internal mental models play a main role: an analysis model to determine assessments based on information obtained from monitoring and a support model to determine proper support actions, taking into account generated assessments. In practice, such internal mental models usually are adaptive in order to improve them over time. Moreover, some form of control is applied. The interplay of these three types of processes involving the mental models (applying them, adapting them and

exerting control) forms a complex and adaptive cognitive process. Modeling such a complex adaptive cognitive process is a nontrivial challenge.

A computational model for the considered cognitive processes can be a tool to study how humans perform them, but it can also be a good basis for an AI-application to support a human. Artificial variants of such cognitive processes are currently being built into new generations of cars as automatic safety systems.

This paper addresses how the complex cognitive processes considered here can be modeled using second-order self-modeling networks [5]. The three elements mentioned (applying the mental models, adapting them and exerting control) are addressed by three levels in such a self-modeling network. At the base level within the self-modeling network model, the internal mental models are modeled and executed; at the first self-modeling level, the adaptation of these mental models is modeled; and at the second self-modeling level, exerted control is modeled.

The work presented in this paper extends the work described in [6] by more than 55% in word count in the following ways:

- The modeling methodology used and model details have been described in much more detail (e.g., the new Section 3).
- The network model in [6] only addressed adaptivity of the excitability of network nodes, but it now has been extended by adding adaptivity for all connections both on the first-order adaptation level and on the second-order adaptation level for control of the first-order adaptation.
- The extended model has been evaluated by simulation experiments of realistic scenarios for twice as many cases.

In this paper, Section 2 briefly introduces self-modeling networks. Section 3 addresses the application domain. Section 4 presents the design of the considered self-modeling network model and Section 5 presents example simulation scenarios of it. Section 6 is a discussion.

2. Network Models Using Self-Models

In this section, the network-oriented modeling approach used from [5, 7] is briefly summarized.

2.1 Distinction between Network Characteristics and Network States

The following is a crucial distinction for network models:

- Network *characteristics* (such as connection weights and excitability thresholds) have values (their strengths) and determine (e.g., cognitive)

processes and behavior in an implicit, automatic manner. They can be considered to provide an *embodiment view* on the network. In principle, these characteristics by themselves may not be directly accessible nor observable for network states (or a person: usually you do not see or feel a specific connection in your brain).

- Network *states* (such as sensor states, sensory representation states, preparation states and emotion states) have values (their activation levels) and are explicit representations that may be accessible for network states or a person and can be handled or manipulated explicitly. They can be considered to provide an *informational view* on the network; usually the states are assumed to have a certain informational content. In principle, for the case of a mental network, states may be accessible or observable for a person: you may see (mental image), feel (emotion) or note in some other way a specific state in your brain.

Following [5, 8], a temporal-causal network model is characterized by (here X and Y denote nodes of the network, also called states):

- *Connectivity characteristics*. Connections from a state X to a state Y and their weights $\omega_{X,Y}$.
- *Aggregation characteristics*. For any state Y , some combination function $c_Y(..)$ defines the aggregation that is applied to the impacts $\omega_{X,Y}X(t)$ on Y from its incoming connections from states X .
- *Timing characteristics*. Each state Y has a speed factor η_Y defining how fast it changes for given impact.

The following difference (or differential) equations that are used for simulation purposes and also for analysis of temporal-causal networks incorporate these network characteristics $\omega_{X,Y}$, $c_Y(..)$, η_Y in a standard numerical format:

$$Y(t + \Delta t) = Y(t) + \eta_Y [c_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) - Y(t)]\Delta t \quad (1)$$

for any state Y and where X_1 to X_k are the states from which Y gets its incoming connections. Here the overall combination function $c_Y(..)$ for state Y is the weighted average of available basic combination functions $c_j(..)$ by specified weights $\gamma_{j,Y}$ (and parameters $\pi_{1,j,Y}$, $\pi_{2,j,Y}$ of $c_j(..)$) for Y :

$$c_Y(V_1, \dots, V_k) = \frac{\gamma_{1,Y}c_1(V_1, \dots, V_k) + \dots + \gamma_{m,Y}c_m(V_1, \dots, V_k)}{\gamma_{1,Y} + \dots + \gamma_{m,Y}}. \quad (2)$$

Such equations (1), (2) and the ones in Table 1 are hidden in the dedicated software environment; see [9, Chapter 9]. Within the software environment described there, a large number of around 40 useful basic combination functions are included in a combination function library; see Table 1 for the first two of them: these are the ones used

in this paper. These concepts enable us to design network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. How it works is that the network characteristics $\omega_{X,Y}$, $\gamma_{j,Y}$, $\pi_{1,j,Y}$, $\pi_{2,j,Y}$, η_Y that define the design of the network model are given as input to the dedicated software environment, and hidden within this environment the difference equations (1) are executed for all states, thus generating simulation graphs as output.

	Notation	Formula	Parameters
Euclidean	$\text{eucl}_{n,\lambda}(V_1, \dots, V_k)$	$\frac{\sqrt[n]{V_1^n + \dots + V_k^n}}{\lambda}$	order $n > 0$ scaling factor $\lambda > 0$
advanced logistic sum	$\text{alogistic}_{\sigma,\tau}(V_1, \dots, V_k)$	$\left[\frac{1}{1 + e^{-\sigma(V_1 + \dots + V_k - \tau)}} - \frac{1}{1 + e^{\sigma\tau}} \right] (1 + e^{-\sigma\tau})$	steepness $\sigma > 0$ excitability threshold τ

Table 1. Basic combination functions from the library used in the model presented here.

2.2 Self-Models Representing Network Characteristics by Network States

The self-modeling network modeling approach is inspired by the more general idea of self-referencing or “mise en abyme,” sometimes also called “the Droste effect” after the famous Dutch chocolate brand that has been using this effect in packaging and advertising of their products since 1904. For some examples, see Figure 1. For more explanation, see for example, [10]. This effect occurs in art when within artwork a small copy of the same artwork is included. This can be applied graphically in paintings or photographs, or in sculptures. Also, it is sometimes used within literature (story-within-the-story), theater (theater-within-the-theater) or movies (movie-within-the-movie).

This idea is applied to network models as follows. As indicated earlier, “network characteristics” and “network states” are two distinct concepts for a network. Self-modeling is a way to relate these distinct concepts to each other in an interesting and useful way:

- A *self-model* is making the implicit network characteristics (such as connection weights and excitability thresholds) explicit by adding states for these characteristics; thus the network gets an internal self-model of part of the network structure of itself.
- In this way, different self-modeling levels can be created where network characteristics from one level relate to explicit network states at the next level. By iteration, an arbitrary number of self-modeling levels can be modeled, covering *second-order or higher-order effects*.



Figure 1. Three examples of the mise en abyme or Droste effect. (Images from: www.hollandwinkel.nl/en/droste-cacao-verpleegster-250-g.html, michel.parpere.pagesperso-orange.fr/pedago/voc/mise%20en%20abyme.htm, www.instagram.com/p/CCYmVLMpGPo.)

Self-modeling networks can be recognized both in physical and mental domains. For example:

- In the *physical domain*, in the brain, information about the characteristics of the network of causal relations between activation states of neurons is, for example, represented in physical configurations for synapses (e.g., connection weights), neurons (e.g., excitability thresholds) and/or chemical substances (e.g., neurotransmitters).
- In the *mental domain*, a person can create mental states in the form of representations of his or her own (personal) characteristics, thus forming a subjective self-model (acquired by experiences); for example, of being very sensitive to pain or to critical feedback or of having an anger issue.

Adding a self-model for a temporal-causal network is done in the way that for some of the states Y of the base network and some of the network structure characteristics for connectivity, aggregation and timing (in particular, some from $\omega_{X,Y}$, $\gamma_{i,Y}$, $\pi_{i,j,Y}$, η_Y), additional network states $W_{X,Y}$, $C_{i,Y}$, $P_{i,j,Y}$, H_Y (self-model states) are introduced (see the blue upper plane in Figure 2 and further):

- (a) Connectivity self-model
- (b) Aggregation self-model
 - Self-model states $P_{i,j,Y}$ are added representing aggregation characteristics, in particular, combination function parameters $\pi_{i,j,Y}$.
- (c) Timing self-model
 - Self-model states $W_{X,Y}$ are added representing connectivity characteristics, in particular, connection weights $\omega_{X,Y}$.

- Self-model states $C_{j,Y}$ are added representing aggregation characteristics, in particular, combination function weights $\gamma_{i,Y}$.
- Self-model states H_Y are added representing timing characteristics, in particular, speed factors η_Y .

The notations $W_{X,Y}$, $C_{i,Y}$, $P_{i,j,Y}$, H_Y for the self-model states indicate the referencing relation with respect to the characteristics $\omega_{X,Y}$, $\gamma_{i,Y}$, $\pi_{i,j,Y}$, η_Y : here W refers to ω , C refers to γ , P refers to π , and H refers to η , respectively. For the processing, these self-model states define the dynamics of state Y in a canonical manner according to equation (1) whereby $\omega_{X,Y}$, $\gamma_{i,Y}$, $\pi_{i,j,Y}$, η_Y are replaced by the state values of $W_{X,Y}$, $C_{i,Y}$, $P_{i,j,Y}$, H_Y at time t , respectively.

An example of an aggregation self-model state $P_{i,j,Y}$ for a combination function parameter $\pi_{i,j,Y}$ is for the excitability threshold τ_Y of state Y , which is the second parameter of the logistic sum combination function; then $P_{i,j,Y}$ is usually indicated by T_Y , which refers to threshold τ_Y . Such aggregation self-model states T_Y will play an important role in the network model addressed in the following, as will connectivity self-model states $W_{X,Y}$, referring to connection weights $\omega_{X,Y}$. Similarly, self-model states H_Y can be added that refer to the speed factor η_Y of Y .

As the outcome of the addition of a self-model is also a temporal-causal network model itself, as has been proven in [9, Chapter 10], this construction can easily be applied iteratively to obtain multiple orders of self-models. This is applied by adding second-order self-model states H_{WT_Y} representing the adaptive speed factors (i.e., adaptive learning rates in this case) for all first-order self-model states T_Y and $W_{X,Y}$, which in turn represent the adaptive threshold τ_Y of Y and the adaptive connection weights $\omega_{X,Y}$ of all incoming connections of Y .

3. Modeling the Adaptation Principles Used

In this section, it will be shown how the modeling approach for self-modeling network models described in Section 2 has been applied to model the adaptation principles of first- and second-order used here. When self-models are changing over time in a proper manner, this offers a useful method to model any adaptation principle. This does not only apply to first-order adaptive networks, but also to second-order adaptive networks, modeling control by using second-order self-models.

3.1 First-Order Self-Models for the First-Order Adaptation Principles Used

Within cognitive neuroscience literature, two types of first-order adaptation are considered, one for connection weights and one for intrinsic neuronal properties; for example, as described in [11, p. 30]:

Quote 1. Learning-related cellular changes can be divided into two general groups: modifications that occur at synapses and modifications in the intrinsic properties of the neurons. While it is commonly agreed that changes in strength of connections between neurons in the relevant networks underlie memory storage, ample evidence suggests that modifications in intrinsic neuronal properties may also account for learning-related behavioral changes.

In this paper, for these two types of adaptivity, two first-order adaptation principles are considered: Hebbian learning for connection weights and excitability modulation for the excitability threshold of states.

The Hebbian Learning Adaptation Principle

A well-known adaptation principle of the first type (addressing adaptive connectivity) is Hebbian learning [12, p. 62], which can be explained by:

Quote 2. When an axon of cell A is near enough to excite B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased.

This is sometimes simplified (neglecting the phrase “one of the cells firing B”) to [13, 14]:

Quote 3. What fires together, wires together.

Within a self-modeling network, this can be modeled by using a *connectivity self-model* based on self-model states $\mathbf{W}_{X,Y}$ representing connection weights $\omega_{X,Y}$. These self-model states need incoming and outgoing connections to let them function within the network. To incorporate the “firing together” part, for the self-model's connectivity, incoming connections from X and Y to $\mathbf{W}_{X,Y}$ are used; see Figure 2 (upward arrows in blue). These upward connections have weight 1 here. Also a connection from $\mathbf{W}_{X,Y}$ to itself with weight 1 is used to model persistence of the learnt effect; in pictures they are usually left out. In addition, an outgoing connection from $\mathbf{W}_{X,Y}$ to state Y is used to indicate where this self-model state $\mathbf{W}_{X,Y}$ has its effect; see Figure 2 (pink downward arrow). The downward connection indicates that the value of $\mathbf{W}_{X,Y}$ is actually used for the connection weight

of the connection from X to Y . For the *aggregation characteristics* of the self-model, one of the options for a learning rule is defined by the combination function $\text{hebb}_\mu(V_1, V_2, W)$ from Table 2; note that $\text{hebb}_\mu(V_1, V_2, W)$ is a similar variant of Hebbian learning for connections with negative weights. For more options of Hebbian learning combination functions and further mathematical analysis of their limit behavior, see, for example [5, Chapter 14].

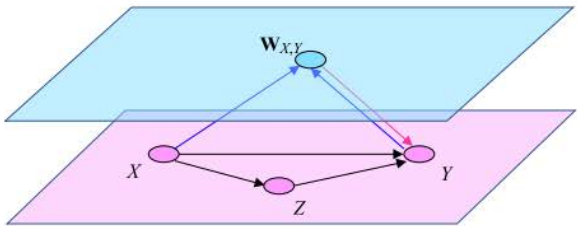


Figure 2. Connectivity characteristics of the self-model for the Hebbian learning adaptation principle.

Name and Self-Model State	Combination Functions	Variables and Parameters
Hebbian learning $W_{X,Y}$	$\text{hebb}_\mu(V_1, V_2, W) = V_1 V_2 (1 - W) + \mu W$ $\text{hebbneg}_\mu(V_1, V_2, W) = -V_1 (1 - V_2) (1 + W) + \mu W$	V_1, V_2 activation levels of connected states W activation level of self-model state $W_{X,Y}$ for connection weight ω , persistence factor
excitability modulation T_Y	$\text{alogistic}_{\sigma,\tau}(V_1, \dots, V_k)$	V_1, \dots, V_k impacts from base states
exposure accelerates adaptation H_{WT_Y}	$\text{alogistic}_{\sigma,\tau}(V_1, \dots, V_k)$	V_1, \dots, V_k impacts from base states and first-order self-model states

Table 2. Combination functions for self-models modeling first- and second-order adaptation principles used here.

The Excitability Modulation Adaptation Principle

Although connectivity adaptation is often addressed in the literature, other characteristics can also be made adaptive, such as excitability thresholds. For example, the following quote indicates that synaptic activity relates to long-lasting modifications in excitability of neurons [11, p. 30]:

Quote 4. Long-lasting modifications in intrinsic excitability are manifested in changes in the neuron's response to a given extrinsic current (generated by synaptic activity or applied via the recording electrode).

For more literature on this form of learning or adaptation (called here the excitability modulation adaptation principle), see [9, 15–19]. As here the adaptation depends on activation of the base states of a state Y and the states X, Z from which it gets its incoming connections, this can be modeled in a self-modeling network in a similar form as earlier using a self-model state T_Y , as shown in Figure 3.

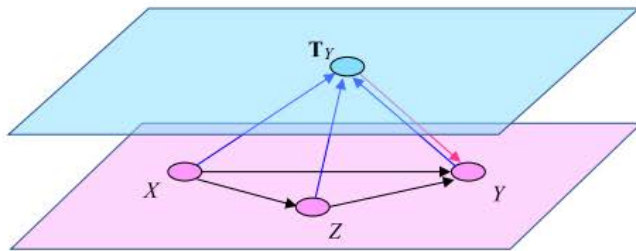


Figure 3. Connectivity characteristics of a self-model for the excitability modulation adaptation principle.

In this case, based on literature such as [9, 11, 15–18] it is assumed that exposure enhances excitability, which means that it decreases the excitability threshold. To achieve this, for the self-model state T_Y a monotonically increasing combination function can be used, while the connection weights from X, Y, Z to T_Y are negative; examples of monotonically increasing combination functions are the logistic sum functions and the Euclidean function (with odd order n) from Table 1. In this case, the (pink) downward connection from T_Y to Y indicates that the value of T_Y is used for the threshold value of the logistic sum function of base state Y .

3.2 Second-Order Self-Model for the Second-Order Adaptation Principle

The first-order adaptation principles discussed in Section 3.1 refer to forms of *plasticity*. It was shown how they can be described by a first-order self-model for connectivity or aggregation characteristics of the base network, in particular for the connection weights and/or the excitability thresholds used in aggregation. Under which circumstances and to which extent such plasticity actually takes place is controlled by a form of so-called *metaplasticity*; for example, [20–25]. Such control can address “the plasticity versus stability

conundrum” (e.g., [25, p. 773]) by only making plasticity happen in circumstances when it is important for the person to change and otherwise stabilize it. Here we consider in particular the following specific second-order adaptation principle for such control of first-order adaptation.

Exposure Accelerates Adaptation Principle

For example, in [23] the following compact quote is found, indicating that increasing stimulus exposure makes the adaptation speed increase [23, p. 2]:

Quote 5. Adaptation accelerates with increasing stimulus exposure.

This indeed describes a form of metaplasticity that controls the speed of adaptation (learning rate). This principle can be modeled by a (dynamic) second-order self-model for timing characteristics (speed factors) of a first-order self-model for the first-order adaptation. Such a second-order self-model is based on self-model states $H_{W_{X,Y}}$ or H_{T_Y} for adaptive learning speed of any of the two types of learning discussed in Section 3.1, or $H_{W_{T_Y}}$ for both types combined. The principle formulated by Quote 5 indicates that the activation level of these second-order self-model states should depend in a monotonically increasing manner on the activation levels of the base states involved: these base states are Y itself and the states X, Z from which Y gets incoming connections. This makes the connectivity of this timing self-model (for both forms of learning) be as shown in Figure 4: the (positive, blue) upward connections from the base states X, Y and Z to the self-model state $H_{W_{T_Y}}$ are used to express the part of the principle in Quote 5 referring to “stimulus exposure.” For the aggregation, for $H_{W_{T_Y}}$, a Euclidean (with odd order n) or a logistic sum function can be used to get the monotonic effect as needed. The (negative, blue) upward connections from $W_{X,Y}$ and T_Y to the self-model state $H_{W_{T_{X,Y}}}$ indicate a counterbalancing effect that makes the learning speed be limited depending on the learned level, as represented by $W_{X,Y}$ and T_Y . The downward (pink) connections from $H_{W_{T_Y}}$ to $W_{X,Y}$ and T_Y indicate that the value of $H_{W_{T_Y}}$ is actually used as a speed factor for $W_{X,Y}$ and T_Y .

This shows how a specific self-modeling network model is obtained according to a more general three-level self-modeling network design for handling internal mental models with the following three levels:

- Base level: applying the mental models (the pink plane in Figure 4).

- First-order adaptation level: adapting the mental models (the blue plane in Figure 4).
- Second-order adaptation level: exerting control over the adaptation of the mental models (the purple plane in Figure 4).

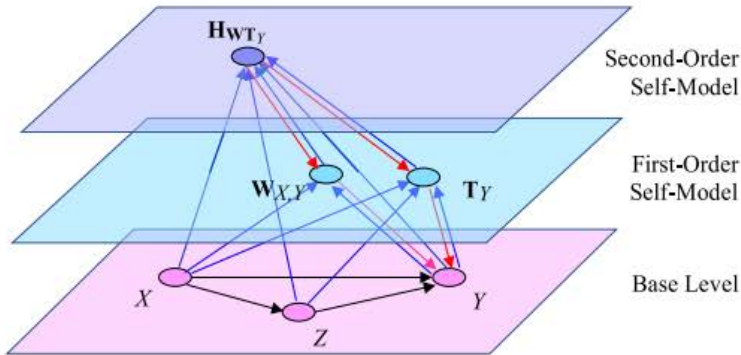


Figure 4. Connectivity of a second-order self-model for the second-order exposure accelerates the adaptation principle for control of first-order self-models for Hebbian learning and excitability modulation.

4. Analysis and Support Processes

In situations where humans perform complex, demanding tasks, it may be better to keep an eye on them to monitor how they are performing and to assess their performance. If performance gets poor, support actions may be considered. The mental processes to determine such assessments and to determine appropriate support actions when needed are complex cognitive processes. In the car driver example considered here, it is assumed that continuous sensor or observation data is available. This may concern information about the driver's alcohol usage, his or her gaze and steering behavior and the amount of rest taken. An unfocused gaze or erratic steering behavior may be assessed as a driving risk. If that assessment occurs, a support action may be needed, such as slowing down the car or advice about that. The knowledge behind these mental processes may be adaptive, enabling the underlying processes to improve over time. Within such complex adaptive cognitive processes, usually internal mental models are used; for example, [1–4]. In the case addressed here, such internal mental models address (see also Figure 5):

- *Analysis model.* This model is used for the assessment of the human's performance using observations (e.g., using specific sensors) and domain knowledge. Examples used in the car driver example are a long

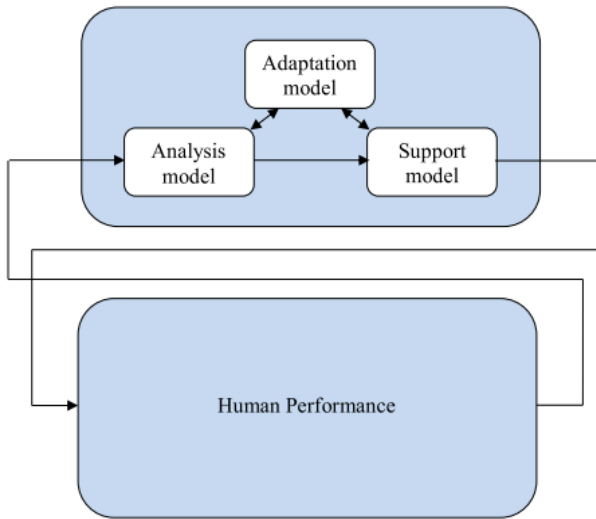


Figure 5. Adaptive model-based architecture to analyze and support humans; adapted from [8, p. 469].

period of driving, a not well-focused gaze, erratic steering and alcohol usage. Examples of generated assessments are a risk for getting exhausted or (other) driving risks.

- *Support model.* This model is used to generate support actions based on the assessments and domain knowledge. Examples of support actions that are generated by this process are advice to take a rest period, blocking the starting of the car (when not driving) and slowing down the car (when driving).

As such processes are in principle adaptive to enable their improvement, a third internal mental model is needed [8, Chapter 16]:

- *Adaptation model.* This model is used to get the analysis and support model to fit the specific characteristics of the situation including the driver and car better. This works via adapting certain characteristics of the internal mental models.

Section 5 addresses how these internal mental models and the way they are used can be modeled by a self-modeling network, leading to the second-order self-modeling network model that is proposed.

5. The Second-Order Adaptive Network Model

This section describes how the modeling approach discussed in Section 2 has been used to model the adaptive mental models for analysis and support of human performance from Section 3 within a self-modeling network.

A useful network architecture to handle internal mental models in general is a self-modeling network that covers at least two levels (see also [26]):

- A base level representing the mental model as a network so that it can be applied or executed (based on the mental model's *within-network dynamics*).
- A first-order self-model explicitly representing the (network) characteristics of the mental model that can be used for formation and adaptation of the mental model (adding *dynamics of the mental model*).

As discussed in Section 3.2, in human processes the extent to which plasticity actually occurs is controlled by a form of metaplasticity; for example, [20–25]. Therefore, a third level (see Section 3.2) is also needed:

- A second-order self-model to control these adaptation processes (control of network adaptation).

This leads to a general three-level network architecture shown in Figure 6, which is applied here; a specific example of this was already shown in Figure 4. Note that by the upward interlevel connections (the blue upward arrows), this general network architecture enables the use of context-specific information from the mental model at the base level for learning and context-specific information from both lower levels for control. This allows us to arrange that both learning and control take place in a context-sensitive manner.

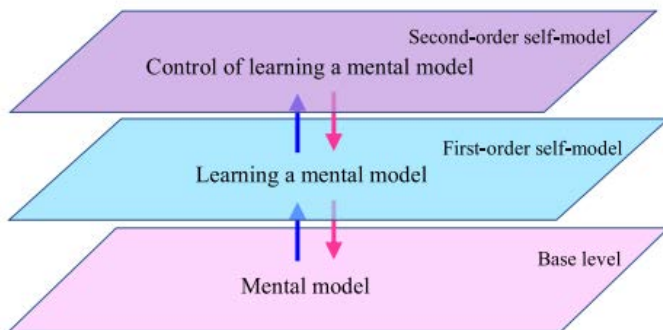


Figure 6. The general three-level network architecture applied.

For reasons of presentation, the introduced model will be discussed in two steps. First, Figure 7 displays the connectivity of the first two levels of the introduced network model: the mental models at the base level within the base (pink) plane and the first-order self-model within the upper (blue) plane. Table 3 provides an overview of all states;

here the states X_1 to X_{10} model the base level and states X_{11} to X_{25} the network's first-order self-model.

5.1 The Base Level

At the base level (see lower pink plane in Figure 7), in the first place a number of context representation states are included: the states for a long duration of driving, alcohol usage, erratic steering and unfocused gaze (X_1 to X_4 , respectively), and for driving (state X_7) in contrast to standing still. These states represent the situation that is considered and are assumed to be available through sensors or observation. In addition, two states (X_5 and X_6) are available for assessments of exhaustion risk and driving risk, and three states (X_8 to X_{10}) for the support actions rest advice, slow down and block start. These assessments have incoming connections from the context representation states (X_1 to X_4) on which they depend, and the support actions have incoming connections from the assessments and from context representation state X_7 for driving. All these connections have adaptive weights $\omega_{X,Y}$. The assessment states and support action states use the combination function $\text{alogistic}_{\sigma,\tau}(\cdot)$, which has an adaptive excitability threshold τ .

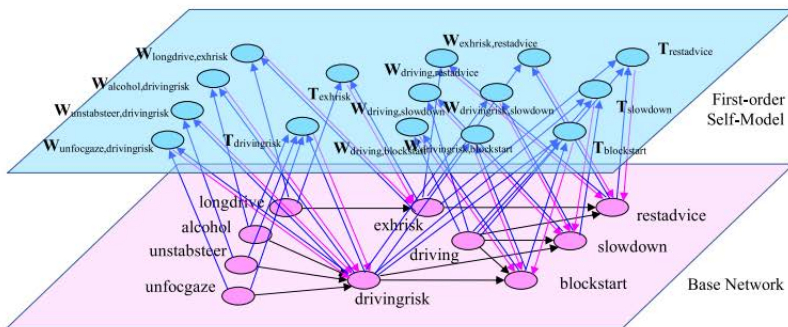


Figure 7. Connectivity for the first two levels of the self-modeling network model.

5.2 First-Order Self-Models

Within the base network, two subnetworks can be distinguished, one for a mental model for analysis to determine an assessment of the performance and one for a mental model to determine support actions. For assessment, for the sake of simplicity the considered scenarios include the two options exhaustiveness risk and driving risk, and for this input information is used on long driving duration, alcohol, erratic steering and unfocused gaze. The mental model for the support

process also uses as input the assessments and generates support actions for which the options are rest advice, slow down and block start. For the two mental models at the base level, self-models have been added that enable adaptation or learning (in the upper plane in Figure 7):

- First-order self-model for the analysis process: first-order self-model W-states and T-states X_{11} to X_{16} in Table 3.
- First-order self-model for the support process: first-order self-model W-states and T-states X_{17} to X_{25} in Table 3.

Name	Explanation
X_1 longdrive	The driver is driving for a long period of time
X_2 alcohol	Alcohol is detected
X_3 unstabsteer	The driver's steering is erratic
X_4 unfogaze	The driver's gaze is not focused
X_5 exhrisk	Assessment of a risk that the driver will get exhausted
X_6 drivingrisk	Assessment of a safety risk for driving
X_7 driving	The car is driving
X_8 restadvice	Supporting action to advise the driver to take some rest
X_9 slowdown	Supporting action to slow down the car
X_{10} blockstart	Supporting action to block the starting of the car
X_{11} $W_{\text{longdrive,exhrisk}}$	First-order connectivity self-model state for weight of the connection from longdrive to exhrisk
X_{12} $W_{\text{alcohol,drivingrisk}}$	First-order connectivity self-model state for weight of the connection from alcohol to drivingrisk
X_{13} $W_{\text{unstabsteer,drivingrisk}}$	First-order connectivity self-model state for weight of the connection from unstabsteer to drivingrisk
X_{14} $W_{\text{unfocgaze,drivingrisk}}$	First-order connectivity self-model state for weight of the connection from longdrive to drivingrisk
X_{15} T_{exhrisk}	First-order aggregation self-model state for excitability threshold of exhrisk
X_{16} $T_{\text{drivingrisk}}$	First-order aggregation self-model state for excitability threshold of drivingrisk
X_{17} $W_{\text{exhrisk,restadvice}}$	First-order connectivity self-model state for weight of the connection from exhrisk to restadvice

Table 3. (*continues*)

Name	Explanation
X_{18} $\mathbf{W}_{\text{driving,restadvice}}$	First-order connectivity self-model state for weight of the connection from driving to restadvice
X_{19} $\mathbf{W}_{\text{drivingrisk,slowdown}}$	First-order connectivity self-model state for weight of the connection from drivingrisk to slowdown
X_{20} $\mathbf{W}_{\text{driving,slowdown}}$	First-order connectivity self-model state for weight of the connection from driving to slowdown
X_{21} $\mathbf{W}_{\text{drivingrisk,blockstart}}$	First-order connectivity self-model state for weight of the connection from drivingrisk to blockstart
X_{22} $\mathbf{W}_{\text{driving,blockstart}}$	First-order connectivity self-model state for weight of the connection from driving to blockstart
X_{23} $\mathbf{T}_{\text{restadvice}}$	First-order aggregation self-model state for excitability threshold of restadvice
X_{24} $\mathbf{T}_{\text{slowdown}}$	First-order aggregation self-model state for excitability threshold of slowdown
X_{25} $\mathbf{T}_{\text{blockstart}}$	First-order aggregation self-model state for excitability threshold of blockstart
X_{26} $\mathbf{W}_{\text{longdrive},\mathbf{T}_{\text{exhrisk}}}$	Second-order connectivity self-model state for weight of the connection from longdrive to $\mathbf{T}_{\text{exhrisk}}$
X_{27} $\mathbf{W}_{\text{exhrisk},\mathbf{T}_{\text{exhrisk}}}$	Second-order connectivity self-model state for weight of the connection from exhrisk to $\mathbf{T}_{\text{exhrisk}}$
X_{28} $\mathbf{W}_{\text{alcohol},\mathbf{T}_{\text{drivingrisk}}}$	Second-order connectivity self-model state for weight of the connection from alcohol to $\mathbf{T}_{\text{drivingrisk}}$
X_{29} $\mathbf{W}_{\text{unstabsteer},\mathbf{T}_{\text{drivingrisk}}}$	Second-order connectivity self-model state for weight of the connection from unstabsteer to $\mathbf{T}_{\text{drivingrisk}}$
X_{30} $\mathbf{W}_{\text{unfocgaze},\mathbf{T}_{\text{drivingrisk}}}$	Second-order connectivity self-model state for weight of the connection from unfocgaze to $\mathbf{T}_{\text{drivingrisk}}$
X_{31} $\mathbf{W}_{\text{drivingrisk},\mathbf{T}_{\text{drivingrisk}}}$	Second-order connectivity self-model state for weight of the connection from drivingrisk to $\mathbf{T}_{\text{drivingrisk}}$
X_{32} $\mathbf{W}_{\text{exhrisk},\mathbf{T}_{\text{restadvice}}}$	Second-order connectivity self-model state for weight of the connection from exhrisk to $\mathbf{T}_{\text{restadvice}}$
X_{33} $\mathbf{W}_{\text{restadvice},\mathbf{T}_{\text{restadvice}}}$	Second-order connectivity self-model state for weight of the connection from restadvice to $\mathbf{T}_{\text{restadvice}}$

Table 3. (continues)

Name	Explanation
$X_{34} \quad \mathbf{W}_{\text{drivingrisk}, T_{\text{slowdown}}}$	Second-order connectivity self-model state for weight of the connection from drivingrisk to T_{slowdown}
$X_{35} \quad \mathbf{W}_{\text{driving}, T_{\text{slowdown}}}$	Second-order connectivity self-model state for weight of the connection from driving to T_{slowdown}
$X_{36} \quad \mathbf{W}_{\text{slowdown}, T_{\text{slowdown}}}$	Second-order connectivity self-model state for weight of the connection from slowdown to T_{slowdown}
$X_{37} \quad \mathbf{W}_{\text{drivingrisk}, T_{\text{blockstart}}}$	Second-order connectivity self-model state for weight of the connection from drivingrisk to $T_{\text{blockstart}}$
$X_{38} \quad \mathbf{W}_{\text{driving}, T_{\text{blockstart}}}$	Second-order connectivity self-model state for weight of the connection from driving to $T_{\text{blockstart}}$
$X_{39} \quad \mathbf{W}_{\text{blockstart}, T_{\text{blockstart}}}$	Second-order connectivity self-model state for weight of the connection from blockstart to $T_{\text{blockstart}}$
$X_{40} \quad \mathbf{H}_{\mathbf{W}T_{\text{exhrisk}}}$	Second-order timing self-model state for the speed of states $\mathbf{W}_{X, \text{exhrisk}}$ and T_{exhrisk}
$X_{41} \quad \mathbf{H}_{\mathbf{W}T_{\text{drivingrisk}}}$	Second-order timing self-model state for the speed of states $\mathbf{W}_{X, \text{drivingrisk}}$ and $T_{\text{drivingrisk}}$
$X_{42} \quad \mathbf{H}_{\mathbf{W}T_{\text{restadvice}}}$	Second-order timing self-model state for the speed of states $\mathbf{W}_{X, \text{restadvice}}$ and $T_{\text{restadvice}}$
$X_{43} \quad \mathbf{H}_{\mathbf{W}T_{\text{slowdown}}}$	Second-order timing self-model state for the speed of states $\mathbf{W}_{X, \text{slowdown}}$ and T_{slowdown}
$X_{44} \quad \mathbf{H}_{\mathbf{W}T_{\text{blockstart}}}$	Second-order timing self-model state for the speed of states $\mathbf{W}_{X, \text{blockstart}}$ and $T_{\text{blockstart}}$

Table 3. Explanation of the states of the second-order self-modeling network model.

These self-models represent the relevant network characteristics for connectivity (\mathbf{W} -states for connection weights) and for aggregation (T -states for excitability thresholds) of the two mental model networks at the base level.

Each of these first-order self-model states $\mathbf{W}_{X,Y}$ and T_Y has a downward connection (in pink) to indicate the state Y of the mental model at the base level for which they have their special effect; so, in relation to these downward links, the value of $\mathbf{W}_{X,Y}$ plays the role of the indicated connection weight and the value of T_Y the role of the indicated excitability threshold. Each of these first-order self-model states $\mathbf{W}_{X,Y}$ and T_Y has upward incoming connections to give it the

relevant information about activation of the base level states, as the adaptation depends on that information via the first-order adaptation principles for Hebbian learning Quotes 2 and 3 and for excitability modulation Quote 5 discussed in Section 3. This enables these self-model states to be dynamic according to the indicated adaptation principles, thereby using the appropriate combination functions as indicated in Table 2.

Note that a negative weight is used for the connections to T_Y from the states within the base level that causally precede the indicated state Y . This makes T_Y get lower values when values of these base level states are higher. To counterbalance this negative effect on T_Y , a positive weight is used for the upward connection from Y itself to T_Y . These two opposite effects create a context-sensitive equilibrium value for each aggregation self-model state T_Y . In this way, each aggregation self-model based on T-states learns and adapts to the context.

5.3 Second-Order Self-Models

To incorporate control of the adaptation, a self-model has been added for the first-order self-models that model the adaptation, as shown (in the purple plane) in Figure 8. This makes the learning (in particular the learning speed) be adaptive itself. As a self-model of a self-model, this is a second-order self-model. Figure 8 displays the connectivity of the complete second-order adaptive network model. The second-order self-model states in this upper (purple) plane are the states exerting control over adaptation:

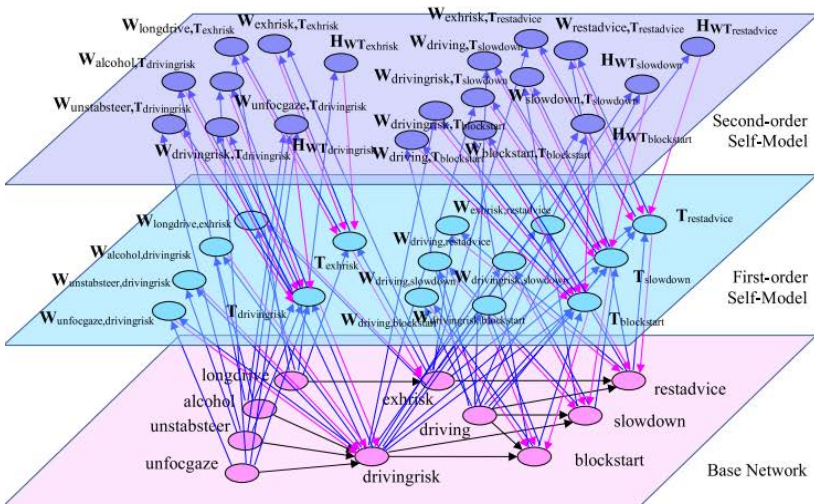


Figure 8. Connectivity of the complete second-order self-modeling network model.

Second-Order Self-Models for the Adaptation Process

Second-order self-model \mathbf{W} -states and $\mathbf{H}_{\mathbf{WT}}$ -states X_{26} to X_{44} in Table 3.

The second-order self-model consists of two parts:

- a second-order *connectivity self-model* using states \mathbf{W}_{X,T_Y} representing the weights of the incoming connections of the \mathbf{T} -states of the first-order self-model
- a second-order *timing self-model* using states $\mathbf{H}_{\mathbf{WT}_Y}$ representing the speed factors of the first-order \mathbf{W} -states and \mathbf{T} -states

These second-order self-models are dynamic, which makes the whole network a second-order adaptive network. To achieve this, the states $\mathbf{H}_{\mathbf{WT}_Y}$ are affected by upward connections from the base level network, following the second-order adaptation principle exposure accelerates adaptation Quote 5 for metaplasticity; for example, [23, 25]. To this end, there are (blue) upward links to each state $\mathbf{H}_{\mathbf{WT}_Y}$ from the base states causally preceding base state Y . As these connections get positive weights, when these causal “antecedents” of Y get higher activation levels, the adaptation speed will increase as well. The special effect of each state $\mathbf{H}_{\mathbf{WT}_Y}$ as a speed factor for states $\mathbf{W}_{X,Y}$ and \mathbf{T}_Y is indicated by the downward (pink) connection to the related state \mathbf{T}_Y .

The states \mathbf{W}_{X,T_Y} in the second-order self-model change according to Hebbian learning Quotes 2 and 3, similar to the states $\mathbf{W}_{X,Y}$ in the first-order self-model as described in Section 5.2. The second-order self-model states $\mathbf{H}_{\mathbf{WT}_Y}$ and \mathbf{W}_{X,T_Y} together exert control over the adaptation process modeled by the first-order self-model. Hereby, the former type of state controls the speed of adaptation (learning rate) and the latter type of state controls which thresholds of the mental models are adapted and how much. All this control takes place in a context-sensitive manner, as via their incoming connections these second-order self-model states are affected by context-specific information from the lower levels.

The appendix with a full specification of the model by role matrices is included in the online version of this paper at content.wolfram.com/uploads/sites/13/2021/12/30-4-3.pdf.

6. Simulation Scenarios

In this section the simulation results for a number of realistic scenarios are discussed. Two different types of scenarios are discussed in Sections 6.1 and 6.2, respectively:

- Only adaptive excitability thresholds, connection weights not adaptive.
- Both adaptive excitability thresholds and adaptive connection weights.

6.1 Using Adaptive Excitability Thresholds and Constant Connection Weights

In Figures 9 to 11, simulation results are shown for three realistic scenarios where the excitability threshold self-model states are dynamic but the connection weight self-model states are not: all connection weight self-model states have constant values assigned. They are defined by the common settings as shown in the role matrices in Appendix A and specific constant values 0 or 1 for the context representation states X_1 to X_4 and X_7 as shown in Table 4. These graphs display the following:

- For the base level: how the assessment is generated by the analysis model and how the support action is generated by the support model.
- For the first-order adaptation level: how the excitability thresholds used within the analysis model and the support model adapt over time.
- For the second-order adaptation or control level: how the adaptation speeds for the adaptations change over time.

Initially the values for the excitability thresholds were set high, in order to illustrate the adaptation process that was needed to get good results. Moreover, the adaptation speed values were initially set at 0. Therefore, in the first phase nothing happens at the base level until the adaptation speeds get higher, making that adaptation process start. In the next phase this results in successful adaptation of the analysis and support models, after which they can generate the appropriate outcomes at the base level.

Scenario		Scenario 1.1 Figure 9	Scenario 1.2 Figure 10	Scenario 1.3 Figure 11
Explanation		driving for too long a time	driving with an unfocused gaze	blocking start after alcohol usage
X_1	longdrive	1	0	0
X_2	alcohol	0	0	1
X_3	unstabsteer	0	0	0
X_4	unfocgaze	0	1	0
X_7	driving	1	1	0

Table 4. The three displayed scenarios.

Scenario 1.1: Driving for Too Long a Time

In Figure 9 for Scenario 1.1, it is shown that by the second-order self-model the adaptation speed for the exhaustion risk excitability threshold increases from time 0 on (see the purple line). This is because the long driving input present from time 0 on works as a stimulus. That the adaptation speed increases with this stimulus is in accordance with the second-order adaptation principle exposure accelerates adaptation [23] discussed in Section 3.2. Moreover, this also conforms to the “plasticity versus stability conundrum” discussed in [25, p. 773]: only adapt (adaptation speed > 0) when relevant, otherwise keep stable (adaptation speed 0). The observed increase in adaptation speed results in actual adaptation of this excitability threshold (conform to Quote 4 from Section 3.1; see [11]): starting at value 2, it decreases to (after time 13) get values between 0.2 and 0.4 (the brown line). It is clear that this is low enough: after time 10 the exhaustion risk assessment is generated and reaches value 1 after time 15 (the pink line). This leads to a successful analysis model outcome.

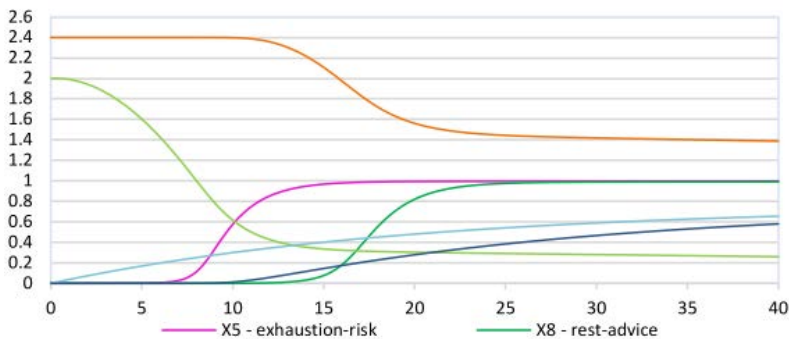


Figure 9. Long drive leads to an exhaustion risk assessment and to the support action rest advice.

In turn this outcome has the result that after time 10 the adaptation model increases the adaptation speed for the excitability threshold of the support action rest advice in the support model (the orange line). This results in actual adaptation of that threshold: the value (initially was 2.4) decreases after time 10 and reaches values between 1.4 and 1.6 after time 18 (the dark purple line). This is low enough, as the support action rest advice comes up after time 18 and reaches 1 after time 25 (the dark green line). This leads to a successful support model outcome.

Scenario 1.2: Driving with an Unfocused Gaze

In Figure 10 for Scenario 1.2, it is shown that by the adaptation model the adaptation speed for the driving risk excitability threshold (within the analysis model) increases from time 0 on (the light blue line). This leads to adaptation of this threshold: starting at value 1.4, it decreases to (after time 7) reach values below 0.7 (the light green line).

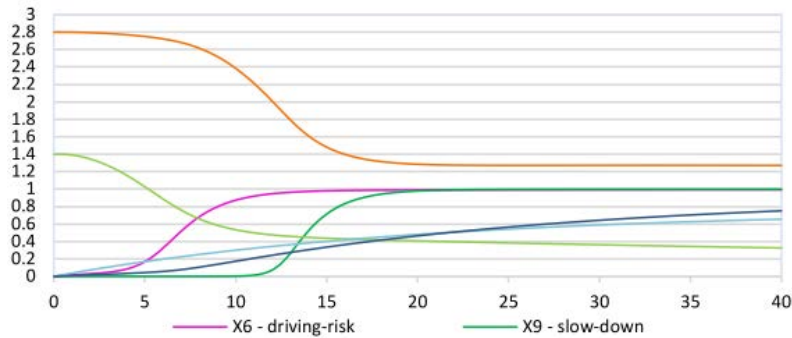


Figure 10. Driving with an unfocused gaze leads to a driving risk assessment and to the support action slow down.

Due to this, from time 5–10 the driving risk assessment is generated and reaches value 1 after time 15 (the pink line). This leads to a successful analysis model outcome. In turn, by the adaptation model, after time 5 the adaptation speed for the excitability threshold of the support action slow down in the support model gets higher (the dark green line). This results in actual adaptation of that threshold: the value that initially was set at 2.8 decreases after time 10 and reaches values between 1.4 and 1.6 after time 18 (middle green line). Due to this, the support action slow down increases after time 18 and reaches 1 after time 20 (the brown line). This leads to a successful support model outcome.

Scenario 1.3: Blocking Start after Alcohol Usage

For Scenario 1.3, Figure 11 shows a similar initial pattern as in Scenario 1.2. However, later on (for the support model), this scenario shows that a fluctuating pattern can also occur. This illustrates how the adaptation of the excitability threshold gets reinforcement from the outcome of the support model, so that in the end they reach an equilibrium according to a fluctuating pattern.

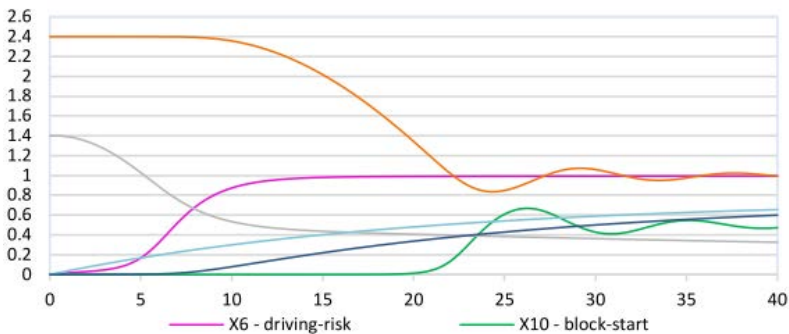


Figure 11. Alcohol usage leads to a driving risk assessment and to the support action block start.

6.2 Using Both Adaptive Excitability Thresholds and Connection Weights

Next, a number of simulations for example scenarios are discussed where not only the excitability thresholds are adaptive but also the connection weights. The role matrices for these scenarios can be found in Appendix B. The values for the context states can be found in Table 5.

			Scenario 2.3, Figures 14 and 15	
Scenario	Scenario 2.1, Figure 12	Scenario 2.2, Figure 13	driving and alcohol	
Explanation	driving too long	driving with erratic steering	nondriving	driving
X ₁ longdrive	1	0	0	0
X ₂ alcohol	0	0	1	1
X ₃ unstabsteer	0	0	0	0
X ₄ unfogaze	0	1	0	0
X ₇ driving	1	1	0	1

Table 5. The three displayed scenarios for double adaptivity.

Scenario 2.1: Driving Too Long

The first scenario addresses a situation in which the driver drives too long without resting. The simulation results of this scenario displayed in Figure 12 show that around time 20 the assessment is made that there is an exhaustion risk (the pink curve) and around time 50 the rest advice support action is generated (the green curve). But before that, different forms of adaptation have taken place. First, triggered

by the exposure from the context information longdrive, the second-order self-model state $H_{WT_exhrisk}$ representing the adaptation speed related to the exhaustion risk assessment X_5 starts to increase from 0 (the light blue curve). By this, it exerts its control on adaptation both on the related excitability thresholds and connection weights. The effect of this on adaptation is seen in two ways. First, the adaptation is seen as the decrease of the excitability threshold for the exhaustion risk assessment X_5 (the light green curve going down from 1). Second, it is seen as the increase of the connection weight representation X_{11} for the connection from long drive X_1 to exhaustion risk X_5 (the dark curve going up to around 0.95, hand in hand with the pink curve for the exhaustion risk). These two adaptations together make the assessment exhaustion risk be generated.

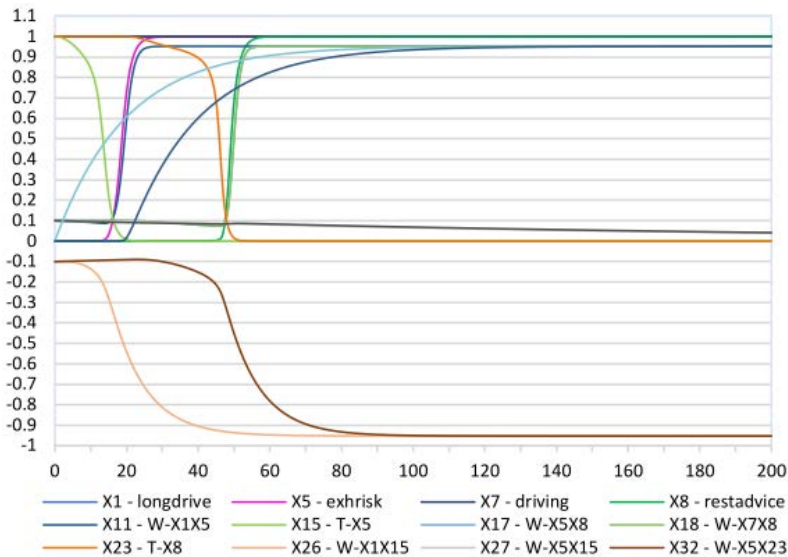


Figure 12. Driving too long leads to a rest advice support action with both adaptive excitability and connectivity.

After this, a similar pattern occurs to generate a support action based on the assessment found. This starts around time 20 with the increase of the second-order self-model state $H_{WT_restadvice}$ representing the adaptation speed related to the rest advice support action, triggered by the assessment found. By the control exerted by this state, again two types of adaptation take place: the threshold representation X_{23} for rest advice X_8 goes down (orange curve) and both connection weight representations X_{17} and X_{18} go up to around 0.95 (both follow the yellow curve).

Note that behind these first-order learning processes, a second-order learning process also takes place, which is displayed by the two curves for X_{26} and X_{32} that go to around -0.95 . Here X_{26} represents the connection weight from X_1 for long drive to X_{15} for the excitability threshold representation for X_5 within the first-order self-model. This exerts a second way of control (in addition to the adaptive first-order adaptation speed) on the first-order adaptation process, as it is this second-order adaptation that enables the threshold of X_5 to be adapted. Similarly, X_{32} represents the connection weight from X_5 for the exhaustion risk assessment to X_{23} for the excitability threshold representation for X_8 within the first-order self-model. This also exerts a second way of control on the first-order adaptation process, as it is this second-order adaptation that enables the threshold of X_8 to be adapted.

Scenario 2.2: Driving with Erratic Steering

The second scenario addresses a situation in which the driver shows erratic steering. The simulation results of this scenario displayed in Figure 13 show that around time 20 the assessment is made that there is a driving risk (the pink curve) and around time 160 the slow down support action is generated (the green curve). As in Scenario 2.1, different forms of adaptation have taken place. First, triggered by the exposure from the context information longdrive, the second-order self-model state $H_{WT_{drivingrisk}}$ representing the adaptation speed related to the driving risk assessment X_5 starts to increase from 0 (the light blue curve). This exerts its control on adaptation of the related excitability thresholds and connection weights. The first adaptation is seen as the decrease of the excitability threshold for the driving risk assessment X_6 (the light green curve going down from 1). Second, it is seen as the increase of the connection weight representation X_{11} for the connection from erratic steering X_3 to driving risk X_6 (the dark curve going up to around 0.95, hand in hand with the pink curve for the driving risk). These two adaptations together lead to the assessment driving risk.

A similar pattern occurs to generate a support action based on the assessment found. This starts around time 25 with the increase of the second-order self-model state $H_{WT_{slowdown}}$ representing the adaptation speed related to the slow down support action, triggered by the assessment found. By the control exerted by this state $H_{WT_{slowdown}}$, again two types of adaptation take place: the threshold representation X_{24} for slow down X_9 goes down (orange curve) and both connection

weight representations X_{19} and X_{20} go up to around 0.95 (both follow the yellow curve).

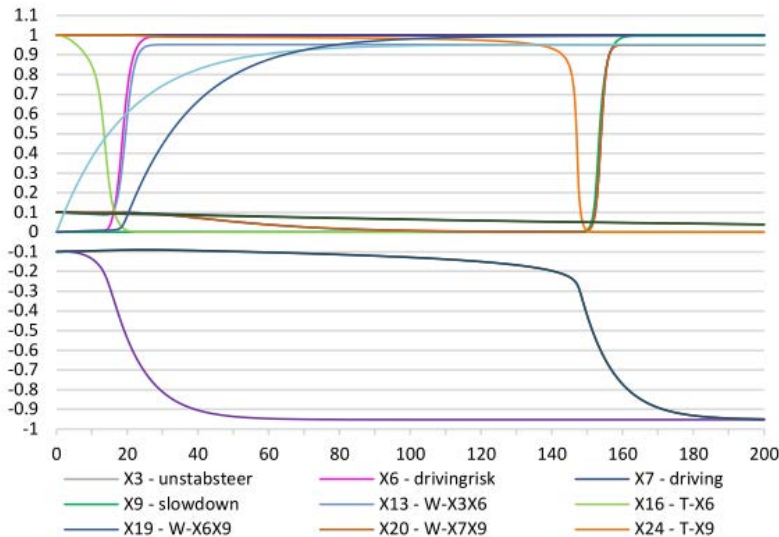


Figure 13. Driving with erratic steering leads to a slow down support action with both adaptive excitability and connectivity.

Again, behind these first-order learning processes, a second-order learning process also takes place, which is displayed by the two curves for X_{29} and X_{35} that go to around -0.95 . Here X_{29} represents the connection weight from X_3 for erratic steering to X_{16} for the excitability threshold representation for driving risk X_6 within the first-order self-model. This exerts an additional means of control on the first-order adaptation process, as it is this second-order adaptation that enables the threshold of X_6 to be adapted. Similarly, X_{34} represents the connection weight from X_6 for the driving risk assessment to X_{24} for the excitability threshold representation for X_9 within the first-order self-model. This also exerts a second means of control on the first-order adaptation process, as it is this second-order adaptation that enables the threshold of X_9 to be adapted.

Scenario 2.3: Driving and Alcohol

The third scenario addresses a situation in which the driver has consumed alcohol. Two cases are considered here (a) the car is not (yet) driving (see Figure 14), and (b) the car is driving (see Figure 15). The simulation results in Figure 14 show that around time 20 the assessment is made that there is a driving risk (the pink curve) and around time 60 the block start support action is generated (the green curve). As in the previous scenarios, different forms of adaptation have taken

place; as it proceeds in a similar manner, this will not be discussed further for this case.

In Figure 15 the other case is addressed: that the car is driving. Here, a different support action, namely slow down, is generated, which occurs around time 150.

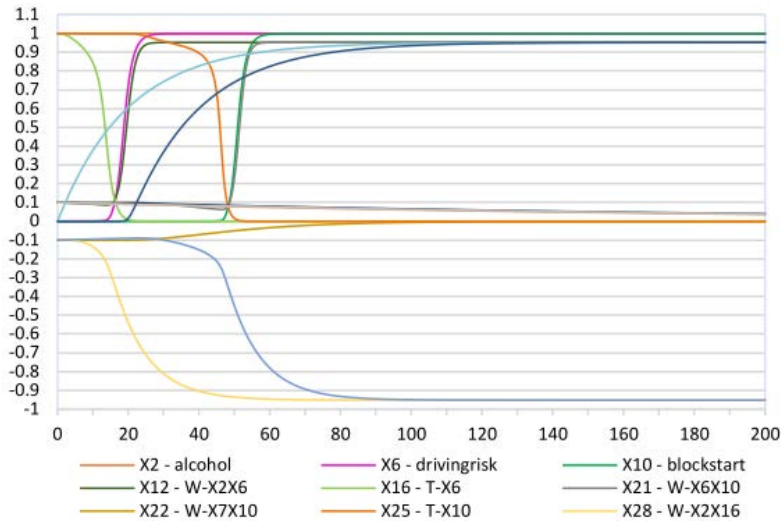


Figure 14. Alcohol usage before intended driving leads to a block start support action with both adaptive excitability and connectivity.

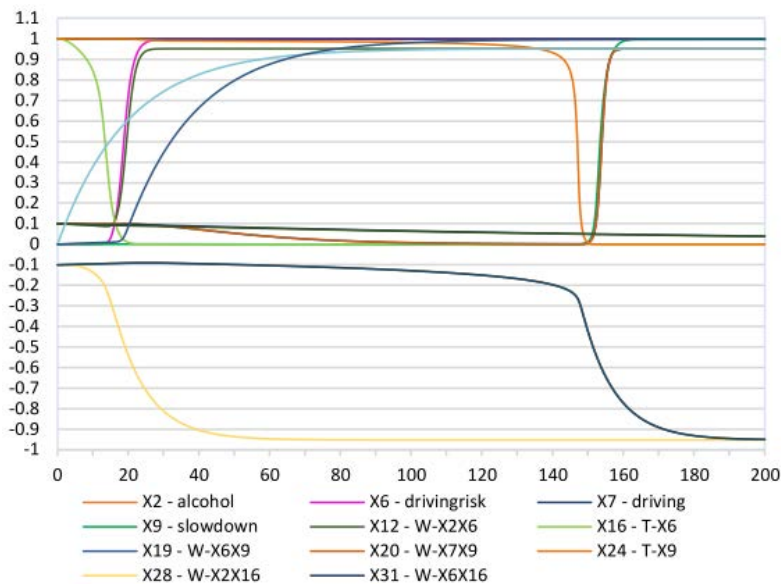


Figure 15. Alcohol usage while driving leads to a slow down support action with both adaptive excitability and connectivity.

7. Discussion

In complex cognitive processes, often internal mental models are used; for example, [1–4]. Such models can just be applied, but they are also often adaptive, in order to form and improve them. The focus in this paper was on adaptive cognitive analysis and support processes for the performance of a human in a demanding task; the adaptive network model was illustrated for a car driver. Within these processes, internal mental models are used for the analysis and support processes.

An adaptive network model was presented that models such adaptive cognitive analysis and support processes. The network model makes use of adaptive first-order self-models for the internal mental models used for the analysis and support processes. To control the adaptation of these first-order self-models, second-order self-models are included. In contrast to the model described in [6] that only addresses adaptivity of excitability thresholds, in the model presented in the current paper, adaptivity of all connection weights is also addressed. The adaptive network model was illustrated for realistic scenarios for a car driver who gets exhausted, shows erratic steering, shows an unfocused gaze and/or used alcohol.

For the adaptivity and its control, the network model makes use of biologically plausible adaptation principles informed by the cognitive neuroscience literature, two within the first-order self-model for adaptation of connectivity and aggregation characteristics of the base network, in particular, concerning connection weights and the excitability thresholds [9–12, 15–19], and two within the second-order self-model for adaptation of connectivity characteristics (connection weights) and timing characteristics (learning rates) for the first-order self-model by metaplasticity [12, 20–25]. This study shows how complex adaptive cognitive processes based on internal mental models, including control of adaptation, can be modeled in an adequate manner by multi-order self-modeling networks.

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Appendix

The appendix with a full specification of the model by role matrices is included in the online version of this paper at content.wolfram.com/uploads/sites/13/2021/12/30-4-3.pdf.

A. Specification of the First Adaptive Network Model by Role Matrices

The first model specification concerns a second-order network model where only the excitability thresholds are adaptive, and not the connection weights. Two combination functions are used, the Euclidean combination function **eucl** and the logistic sum combination function **alogistic** (see Table 1).

Role matrices provide an overview of the different types of factors that causally affect the network states. In each of the role matrices, each state X_i in the network has its own row where it is listed which other states or characteristics affect this state from that role. For example, in Figure A.1 role matrix **mb** (for base connectivity) indicates which other states affect a given state X_i (because there are incoming connections from them). In Figure A.2 role matrix **mcw** (for connection weights) indicates what the connection weights of these connections are. Together, these role matrices **mb** and **mcw** define the *connectivity characteristics* of the network model. Moreover, in Figure A.3 role matrix **mcfw** (for combination function weights) indicates how a given state X_i is affected by the choice of combination function(s) made for this state. Figure A.4 shows role matrix **mcfp** (for combination function parameters) indicates the parameters for these combination functions. Together, role matrices **mcfw** and **mcfp** define the *aggregation characteristics* of the network model. Finally, Figure A.5 shows how the *timing characteristics* of the network model are defined by role matrix **ms** (for speed factors). In the nonempty cells in role matrices there is either a static value or a pointer (reference) to a state that represents this value in a dynamic manner as a self-model state. The latter option is the detailed specification of what in the three-dimensional images are the pink downward arrows. It specifies the specific role of the causal effect; this provides a quite compact specification of the different self-model levels. For more information on role matrices, see [5].

For the first network model specification, for connectivity characteristics all connection weights not determined by \mathbf{W} -states are 1, except for the connection from driving to $\mathbf{H}_{\mathbf{WT}_{\text{blockstart}}}$, which is -1 . For aggregation characteristics, the logistic sum combination function (see Table 1) is used for the base states for assessment and support options (with steepness $\sigma = 8$ and adaptive excitability threshold) and the second-order $\mathbf{H}_{\mathbf{WT}}$ -states (with steepness $\sigma = 4$ and excitability threshold $\tau = 0.7$ or 1.4 depending on the number of incoming connections). All other states use the Euclidean combination function (see Table 1) with $n = 1$ and $\lambda = 1$, which actually is just a sum function. For timing characteristics, the speed factors of the base states for assessment and support options are 0.5 and for the second-order $\mathbf{H}_{\mathbf{WT}}$ -states 0.05 . All other speed factors are adaptive (the base states

for assessment and support options) or 0 (for the other base states and for all **W**-states). The initial values for all **W**-states (which are kept constant due to the speed factor value 0) are 1 when they represent a positive connection; negative ones are:

$$\begin{aligned} &W_{\text{driving,blockstart}}, \\ &W_{\text{longdrive},T_{\text{exhrisk}}}, \\ &W_{\text{alcohol},T_{\text{drivingrisk}}}, \\ &W_{\text{unstabsteer},T_{\text{drivingrisk}}}, \\ &W_{\text{unfocgaze},T_{\text{drivingrisk}}}, \\ &W_{\text{exhrisk},T_{\text{restadvice}}} \end{aligned}$$

which have initial value -1, and

$$\begin{aligned} &W_{\text{drivingrisk},T_{\text{slowdown}}}, \\ &W_{\text{driving},T_{\text{slowdown}}}, \\ &W_{\text{drivingrisk},T_{\text{blockstart}}}, \\ &W_{\text{driving},T_{\text{blockstart}}} \end{aligned}$$

with initial value -0.5. The initial values of all **H_{WT}**-states are 0 as they are for all base states except the observables shown in Figure A.5, which depend on the chosen scenario. Finally, the initial values for the five **T**-states were on purpose set on too-high values 2, 1.4, 2.4, 2.8, 2.4, respectively (in relation to the number of their incoming connections), in order to let adaptation happen.

mb base connectivity		1	2	3	4	5
X ₁	longdrive	X ₁				
X ₂	alcohol	X ₂				
X ₃	unstabsteer	X ₃				
X ₄	unfocgaze	X ₄				
X ₅	exhrisk	X ₁				
X ₆	drivingrisk	X ₂	X ₃	X ₄		
X ₇	driving	X ₇				
X ₈	restadvice	X ₅	X ₇			
X ₉	slowdown	X ₆	X ₇			
X ₁₀	blockstart	X ₆	X ₇			
X ₁₁	W _{longdrive,exhrisk}	X ₁₁				
X ₁₂	W _{alcohol,drivingrisk}	X ₁₂				
X ₁₃	W _{unstabsteer,drivingrisk}	X ₁₃				
X ₁₄	W _{unfocgaze,drivingrisk}	X ₁₄				

mb base connectivity		1	2	3	4	5
X ₁₅	T _{exhrisk}	X ₁	X ₅	X ₁₅		
X ₁₆	T _{drivingrisk}	X ₂	X ₃	X ₄	X ₆	X ₁₆
X ₁₇	W _{exhrisk,restadvice}	X ₁₇				
X ₁₈	W _{driving,restadvice}	X ₁₈				
X ₁₉	W _{drivingrisk,slowdown}	X ₁₉				
X ₂₀	W _{driving,slowdown}	X ₂₀				
X ₂₁	W _{drivingrisk,blockstart}	X ₂₁				
X ₂₂	W _{driving,blockstart}	X ₂₂				
X ₂₃	T _{restadvice}	X ₅	X ₈	X ₂₃		
X ₂₄	T _{slowdown}	X ₆	X ₇	X ₉	X ₂₄	
X ₂₅	T _{blockstart}	X ₆	X ₇	X ₁₀	X ₂₅	
X ₂₆	W _{longdrive,T_{exhrisk}}	X ₂₆				
X ₂₇	W _{exhrisk,T_{exhrisk}}	X ₂₇				
X ₂₈	W _{alcohol,T_{drivingrisk}}	X ₂₈				
X ₂₉	W _{unstabsteer,T_{drivingrisk}}	X ₂₉				
X ₃₀	W _{unfocgaze,T_{drivingrisk}}	X ₃₀				
X ₃₁	W _{drivingrisk,T_{drivingrisk}}	X ₃₁				
X ₃₂	W _{exhrisk,T_{restadvice}}	X ₃₂				
X ₃₃	W _{restadvice,T_{restadvice}}	X ₃₃				
X ₃₄	W _{drivingrisk,T_{slowdown}}	X ₃₄				
X ₃₅	W _{driving,T_{slowdown}}	X ₃₅				
X ₃₆	W _{slowdown,T_{slowdown}}	X ₃₆				
X ₃₇	W _{drivingrisk,T_{blockstart}}	X ₃₇				
X ₃₈	W _{driving,T_{blockstart}}	X ₃₈				
X ₃₉	W _{blockstart,T_{blockstart}}	X ₃₉				
X ₄₀	H _{T_{exhrisk}}	X ₁				
X ₄₁	H _{T_{drivingrisk}}	X ₂	X ₃	X ₄		
X ₄₂	H _{T_{restadvice}}	X ₅				
X ₄₃	H _{T_{slowdown}}	X ₆	X ₇			
X ₄₄	H _{T_{blockstart}}	X ₆	X ₇			

Figure A.1. Role matrices specifying *connectivity* characteristics: **mb** for base connections.

mcw connection weights		1	2	3	4	5
X_1	longdrive	1				
X_2	alcohol	1				
X_3	unstabsteer	1				
X_4	unfocgaze	1				
X_5	exhrisk	X_{11}				
X_6	drivingrisk	X_{12}	X_{13}	X_{14}		
X_7	driving	1				
X_8	restadvice	X_{17}	X_{18}			
X_9	slowdown	X_{19}	X_{20}			
X_{10}	blockstart	X_{21}	X_{22}			
X_{11}	$W_{\text{longdrive,exhrisk}}$	1				
X_{12}	$W_{\text{alcohol,drivingrisk}}$	1				
X_{13}	$W_{\text{unstabsteer,drivingrisk}}$	1				
X_{14}	$W_{\text{unfocgaze,drivingrisk}}$	1				
X_{15}	T_{exhrisk}	X_{26}	X_{27}	1		
X_{16}	$T_{\text{drivingrisk}}$	X_{28}	X_{29}	X_{30}	X_{31}	1
X_{17}	$W_{\text{exhrisk,restadvice}}$	1				
X_{18}	$W_{\text{driving,restadvice}}$	1				
X_{19}	$W_{\text{drivingrisk,slowdown}}$	1				
X_{20}	$W_{\text{driving,slowdown}}$	1				
X_{21}	$W_{\text{drivingrisk,blockstart}}$	1				
X_{22}	$W_{\text{driving,blockstart}}$	1				
X_{23}	$T_{\text{restadvice}}$	X_{32}	X_{33}	1		
X_{24}	T_{slowdown}	X_{34}	X_{35}	X_{36}	1	
X_{25}	$T_{\text{blockstart}}$	X_{37}	X_{38}	X_{39}	1	
X_{26}	$W_{\text{longdrive},T_{\text{exhrisk}}}$	1				
X_{27}	$W_{\text{exhrisk},T_{\text{exhrisk}}}$	1				
X_{28}	$W_{\text{alcohol},T_{\text{drivingrisk}}}$	1				
X_{29}	$W_{\text{unstabsteer},T_{\text{drivingrisk}}}$	1				
X_{30}	$W_{\text{unfocgaze},T_{\text{drivingrisk}}}$	1				
X_{31}	$W_{\text{drivingrisk},T_{\text{drivingrisk}}}$	1				
X_{32}	$W_{\text{exhrisk},T_{\text{restadvice}}}$	1				
X_{33}	$W_{\text{restadvice},T_{\text{restadvice}}}$	1				

mcw connection weights		1	2	3	4	5
X_{34}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{slowdown}}}$	1				
X_{35}	$\mathbf{W}_{\text{driving}, T_{\text{slowdown}}}$	1				
X_{36}	$\mathbf{W}_{\text{slowdown}, T_{\text{slowdown}}}$	1				
X_{37}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{blockstart}}}$	1				
X_{38}	$\mathbf{W}_{\text{driving}, T_{\text{blockstart}}}$	1				
X_{39}	$\mathbf{W}_{\text{blockstart}, T_{\text{blockstart}}}$	1				
X_{40}	$\mathbf{H}_{T_{\text{exhrisk}}}$	1				
X_{41}	$\mathbf{H}_{T_{\text{drivingrisk}}}$	1	1	1		
X_{42}	$\mathbf{H}_{T_{\text{restadvice}}}$	1				
X_{43}	$\mathbf{H}_{T_{\text{slowdown}}}$	1	1			
X_{44}	$\mathbf{H}_{T_{\text{blockstart}}}$	1	-1			

Figure A.2. Role matrices specifying *connectivity* characteristics: mcw for con-
nection weights.

mcfw function combination weights		1 eucl	2 logistic
X_1	longdrive	1	
X_2	alcohol	1	
X_3	unstabsteer	1	
X_4	unfocgaze	1	
X_5	exhrisk		1
X_6	drivingrisk		1
X_7	driving	1	
X_8	restadvice		1
X_9	slowdown		1
X_{10}	blockstart		1
X_{11}	$\mathbf{W}_{\text{longdrive}, \text{exhrisk}}$	1	
X_{12}	$\mathbf{W}_{\text{alcohol}, \text{drivingrisk}}$	1	
X_{13}	$\mathbf{W}_{\text{unstabsteer}, \text{drivingrisk}}$	1	
X_{14}	$\mathbf{W}_{\text{unfocgaze}, \text{drivingrisk}}$	1	
X_{15}	$\mathbf{T}_{\text{exhrisk}}$	1	
X_{16}	$\mathbf{T}_{\text{drivingrisk}}$	1	

mcfw	function combination weights	1 eucl	2 alogistic
X_{17}	$W_{\text{exhrisk, restadvice}}$	1	
X_{18}	$W_{\text{driving, restadvice}}$	1	
X_{19}	$W_{\text{drivingrisk, slowdown}}$	1	
X_{20}	$W_{\text{driving, slowdown}}$	1	
X_{21}	$W_{\text{drivingrisk, blockstart}}$	1	
X_{22}	$W_{\text{driving, blockstart}}$	1	
X_{23}	$T_{\text{restadvice}}$	1	
X_{24}	T_{slowdown}	1	
X_{25}	$T_{\text{blockstart}}$	1	
X_{26}	$W_{\text{longdrive, } T_{\text{exhrisk}}}$	1	
X_{27}	$W_{\text{exhrisk, } T_{\text{exhrisk}}}$	1	
X_{28}	$W_{\text{alcohol, } T_{\text{drivingrisk}}}$	1	
X_{29}	$W_{\text{unstabsteer, } T_{\text{drivingrisk}}}$	1	
X_{30}	$W_{\text{unfocgaze, } T_{\text{drivingrisk}}}$	1	
X_{31}	$W_{\text{drivingrisk, } T_{\text{drivingrisk}}}$	1	
X_{32}	$W_{\text{exhrisk, } T_{\text{restadvice}}}$	1	
X_{33}	$W_{\text{restadvice, } T_{\text{restadvice}}}$	1	
X_{34}	$W_{\text{drivingrisk, } T_{\text{slowdown}}}$	1	
X_{35}	$W_{\text{driving, } T_{\text{slowdown}}}$	1	
X_{36}	$W_{\text{slowdown, } T_{\text{slowdown}}}$	1	
X_{37}	$W_{\text{drivingrisk, } T_{\text{blockstart}}}$	1	
X_{38}	$W_{\text{driving, } T_{\text{blockstart}}}$	1	
X_{39}	$W_{\text{blockstart, } T_{\text{blockstart}}}$	1	
X_{40}	$H_{T_{\text{exhrisk}}}$		1
X_{41}	$H_{T_{\text{drivingrisk}}}$		1
X_{42}	$H_{T_{\text{restadvice}}}$		1
X_{43}	$H_{T_{\text{slowdown}}}$		1
X_{44}	$H_{T_{\text{blockstart}}}$		1

Figure A.3. Role matrices specifying *aggregation* characteristics: mcfw for combination function weights.

mcfp combination function parameters		1 eucl		2 logistic	
		1 <i>n</i>	2 <i>λ</i>	1 <i>σ</i>	2 <i>τ</i>
<i>X</i> ₁	longdrive	1	1		
<i>X</i> ₂	alcohol	1	1		
<i>X</i> ₃	unstabsteer	1	1		
<i>X</i> ₄	unfocgaze	1	1		
<i>X</i> ₅	exhrisk			8	<i>X</i> ₁₅
<i>X</i> ₆	drivingrisk			8	<i>X</i> ₁₆
<i>X</i> ₇	driving	1	1		
<i>X</i> ₈	restadvice			8	<i>X</i> ₂₃
<i>X</i> ₉	slowdown			8	<i>X</i> ₂₄
<i>X</i> ₁₀	blockstart			8	<i>X</i> ₂₅
<i>X</i> ₁₁	<i>W</i> _{longdrive, exhrisk}	1	1		
<i>X</i> ₁₂	<i>W</i> _{alcohol, drivingrisk}	1	1		
<i>X</i> ₁₃	<i>W</i> _{unstabsteer, drivingrisk}	1	1		
<i>X</i> ₁₄	<i>W</i> _{unfocgaze, drivingrisk}	1	1		
<i>X</i> ₁₅	<i>T</i> _{exhrisk}	1	1		
<i>X</i> ₁₆	<i>T</i> _{drivingrisk}	1	1		
<i>X</i> ₁₇	<i>W</i> _{exhrisk, restadvice}	1	1		
<i>X</i> ₁₈	<i>W</i> _{driving, restadvice}	1	1		
<i>X</i> ₁₉	<i>W</i> _{drivingrisk, slowdown}	1	1		
<i>X</i> ₂₀	<i>W</i> _{driving, slowdown}	1	1		
<i>X</i> ₂₁	<i>W</i> _{drivingrisk, blockstart}	1	1		
<i>X</i> ₂₂	<i>W</i> _{driving, blockstart}	1	1		
<i>X</i> ₂₃	<i>T</i> _{restadvice}	1	1		
<i>X</i> ₂₄	<i>T</i> _{slowdown}	1	1		
<i>X</i> ₂₅	<i>T</i> _{blockstart}	1	1		
<i>X</i> ₂₆	<i>W</i> _{longdrive, <i>T</i>_{exhrisk}}	1	1		
<i>X</i> ₂₇	<i>W</i> _{exhrisk, <i>T</i>_{exhrisk}}	1	1		
<i>X</i> ₂₈	<i>W</i> _{alcohol, <i>T</i>_{drivingrisk}}	1	1		
<i>X</i> ₂₉	<i>W</i> _{unstabsteer, <i>T</i>_{drivingrisk}}	1	1		

mcfp combination function parameters		1 eucl		2 logistic	
		1 n	2 λ	1 σ	2 τ
X_{30}	$\mathbf{W}_{\text{unfocgaze}, T_{\text{drivingrisk}}}$	1	1		
X_{31}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{drivingrisk}}}$	1	1		
X_{32}	$\mathbf{W}_{\text{exhrisk}, T_{\text{restadvice}}}$	1	1		
X_{33}	$\mathbf{W}_{\text{restadvice}, T_{\text{restadvice}}}$	1	1		
X_{34}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{slowdown}}}$	1	1		
X_{35}	$\mathbf{W}_{\text{driving}, T_{\text{slowdown}}}$	1	1		
X_{36}	$\mathbf{W}_{\text{slowdown}, T_{\text{slowdown}}}$	1	1		
X_{37}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{blockstart}}}$	1	1		
X_{38}	$\mathbf{W}_{\text{driving}, T_{\text{blockstart}}}$	1	1		
X_{39}	$\mathbf{W}_{\text{blockstart}, T_{\text{blockstart}}}$	1	1		
X_{40}	$\mathbf{H}_{T_{\text{exhrisk}}}$			4	0.7
X_{41}	$\mathbf{H}_{T_{\text{drivingrisk}}}$			4	0.7
X_{42}	$\mathbf{H}_{T_{\text{restadvice}}}$			4	0.7
X_{43}	$\mathbf{H}_{T_{\text{slowdown}}}$			4	1.4
X_{44}	$\mathbf{H}_{T_{\text{blockstart}}}$			4	0.7

Figure A.4. Role matrices specifying *aggregation* characteristics: **mcfp** for combination function parameters.

ms speed factors			1	iv initial values			1
X_1	longdrive		0	X_1	longdrive		0
X_2	alcohol		0	X_2	alcohol		0
X_3	unstabsteer		0	X_3	unstabsteer		0
X_4	unfocgaze		0	X_4	unfocgaze		0
X_5	exhrisk		0.5	X_5	exhrisk		0
X_6	drivingrisk		0.5	X_6	drivingrisk		0
X_7	driving		0	X_7	driving		0
X_8	restadvice		0.5	X_8	restadvice		0
X_9	slowdown		0.5	X_9	slowdown		0
X_{10}	blockstart		0.5	X_{10}	blockstart		0
X_{11}	$\mathbf{W}_{\text{longdrive}, \text{exhrisk}}$		0	X_{11}	$\mathbf{W}_{\text{longdrive}, \text{exhrisk}}$		1
X_{12}	$\mathbf{W}_{\text{alcohol}, \text{drivingrisk}}$		0	X_{12}	$\mathbf{W}_{\text{alcohol}, \text{drivingrisk}}$		1
X_{13}	$\mathbf{W}_{\text{unstabsteer}, \text{drivingrisk}}$		0	X_{13}	$\mathbf{W}_{\text{unstabsteer}, \text{drivingrisk}}$		1

ms speed factors		1	iv initial values		1
X_{14}	$W_{\text{unfocgaze,drivingrisk}}$	0	X_{14}	$W_{\text{unfocgaze,drivingrisk}}$	1
X_{15}	T_{exhrisk}	X_{40}	X_{15}	T_{exhrisk}	2
X_{16}	$T_{\text{drivingrisk}}$	X_{41}	X_{16}	$T_{\text{drivingrisk}}$	1.4
X_{17}	$W_{\text{exhrisk,restadvice}}$	0	X_{17}	$W_{\text{exhrisk,restadvice}}$	1
X_{18}	$W_{\text{driving,restadvice}}$	0	X_{18}	$W_{\text{driving,restadvice}}$	1
X_{19}	$W_{\text{drivingrisk,slowdown}}$	0	X_{19}	$W_{\text{drivingrisk,slowdown}}$	1
X_{20}	$W_{\text{driving,slowdown}}$	0	X_{20}	$W_{\text{driving,slowdown}}$	1
X_{21}	$W_{\text{drivingrisk,blockstart}}$	0	X_{21}	$W_{\text{drivingrisk,blockstart}}$	1
X_{22}	$W_{\text{driving,blockstart}}$	0	X_{22}	$W_{\text{driving,blockstart}}$	-1
X_{23}	$T_{\text{restadvice}}$	X_{42}	X_{23}	$T_{\text{restadvice}}$	2.4
X_{24}	T_{slowdown}	X_{43}	X_{24}	T_{slowdown}	2.8
X_{25}	$T_{\text{blockstart}}$	X_{44}	X_{25}	$T_{\text{blockstart}}$	2.4
X_{26}	$W_{\text{longdrive},T_{\text{exhrisk}}}$	0	X_{26}	$W_{\text{longdrive},T_{\text{exhrisk}}}$	-1
X_{27}	$W_{\text{exhrisk},T_{\text{exhrisk}}}$	0	X_{27}	$W_{\text{exhrisk},T_{\text{exhrisk}}}$	1
X_{28}	$W_{\text{alcohol},T_{\text{drivingrisk}}}$	0	X_{28}	$W_{\text{alcohol},T_{\text{drivingrisk}}}$	-1
X_{29}	$W_{\text{unstabsteer},T_{\text{drivingrisk}}}$	0	X_{29}	$W_{\text{unstabsteer},T_{\text{drivingrisk}}}$	-1
X_{30}	$W_{\text{unfocgaze},T_{\text{drivingrisk}}}$	0	X_{30}	$W_{\text{unfocgaze},T_{\text{drivingrisk}}}$	-1
X_{31}	$W_{\text{drivingrisk},T_{\text{drivingrisk}}}$	0	X_{31}	$W_{\text{drivingrisk},T_{\text{drivingrisk}}}$	1
X_{32}	$W_{\text{exhrisk},T_{\text{restadvice}}}$	0	X_{32}	$W_{\text{exhrisk},T_{\text{restadvice}}}$	-1
X_{33}	$W_{\text{restadvice},T_{\text{restadvice}}}$	0	X_{33}	$W_{\text{restadvice},T_{\text{restadvice}}}$	1
X_{34}	$W_{\text{drivingrisk},T_{\text{slowdown}}}$	0	X_{34}	$W_{\text{drivingrisk},T_{\text{slowdown}}}$	-0.5
X_{35}	$W_{\text{driving},T_{\text{slowdown}}}$	0	X_{35}	$W_{\text{driving},T_{\text{slowdown}}}$	-0.5
X_{36}	$W_{\text{slowdown},T_{\text{slowdown}}}$	0	X_{36}	$W_{\text{slowdown},T_{\text{slowdown}}}$	1
X_{37}	$W_{\text{drivingrisk},T_{\text{blockstart}}}$	0	X_{37}	$W_{\text{drivingrisk},T_{\text{blockstart}}}$	-0.5
X_{38}	$W_{\text{driving},T_{\text{blockstart}}}$	0	X_{38}	$W_{\text{driving},T_{\text{blockstart}}}$	-0.5
X_{39}	$W_{\text{blockstart},T_{\text{blockstart}}}$	0	X_{39}	$W_{\text{blockstart},T_{\text{blockstart}}}$	1
X_{40}	$H_{T_{\text{exhrisk}}}$	0.05	X_{40}	$H_{T_{\text{exhrisk}}}$	0
X_{41}	$H_{T_{\text{drivingrisk}}}$	0.05	X_{41}	$H_{T_{\text{drivingrisk}}}$	0
X_{42}	$H_{T_{\text{restadvice}}}$	0.05	X_{42}	$H_{T_{\text{restadvice}}}$	0
X_{43}	$H_{T_{\text{slowdown}}}$	0.05	X_{43}	$H_{T_{\text{slowdown}}}$	0
X_{44}	$H_{T_{\text{blockstart}}}$	0.05	X_{44}	$H_{T_{\text{blockstart}}}$	0

Figure A.5. Role matrix *ms* specifying *timing* characteristics and vector *iv* of initial values.

B. Role Matrices Specification of the Second Adaptive Network Model

The second network model specification concerns a second-order network model where not only are the excitability thresholds adaptive, but also the connection weights (Figures B.1 and B.2).

mb base connectivity		1	2	3	4	5
X_1	longdrive	X_1				
X_2	alcohol	X_2				
X_3	unstabsteer	X_3				
X_4	unfocgaze	X_4				
X_5	exhrisk	X_1				
X_6	drivingrisk	X_2	X_3	X_4		
X_7	driving	X_7				
X_8	restadvice	X_5	X_7			
X_9	slowdown	X_6	X_7			
X_{10}	blockstart	X_6	X_7			
X_{11}	$W_{\text{longdrive,exhrisk}}$	X_1	X_5	X_{11}		
X_{12}	$W_{\text{alcohol,drivingrisk}}$	X_2	X_6	X_{12}		
X_{13}	$W_{\text{unstabsteer,drivingrisk}}$	X_3	X_6	X_{13}		
X_{14}	$W_{\text{unfocgaze,drivingrisk}}$	X_4	X_6	X_{14}		
X_{15}	T_{exhrisk}	X_1	X_5	X_{15}		
X_{16}	$T_{\text{drivingrisk}}$	X_2	X_3	X_4	X_6	X_{16}
X_{17}	$W_{\text{exhrisk,restadvice}}$	X_5	X_8	X_{17}		
X_{18}	$W_{\text{driving,restadvice}}$	X_7	X_8	X_{18}		
X_{19}	$W_{\text{drivingrisk,slowdown}}$	X_6	X_9	X_{19}		
X_{20}	$W_{\text{driving,slowdown}}$	X_7	X_9	X_{20}		
X_{21}	$W_{\text{drivingrisk,blockstart}}$	X_6	X_{10}	X_{21}		
X_{22}	$W_{\text{driving,blockstart}}$	X_7	X_{10}	X_{22}		
X_{23}	$T_{\text{restadvice}}$	X_5	X_8	X_{23}		
X_{24}	T_{slowdown}	X_6	X_7	X_9	X_{24}	
X_{25}	$T_{\text{blockstart}}$	X_6	X_7	X_{10}	X_{25}	
X_{26}	$W_{\text{longdrive},T_{\text{exhrisk}}}$	X_1	X_{15}	X_{26}		
X_{27}	$W_{\text{exhrisk},T_{\text{exhrisk}}}$	X_5	X_{15}	X_{27}		
X_{28}	$W_{\text{alcohol},T_{\text{drivingrisk}}}$	X_2	X_{16}	X_{28}		
X_{29}	$W_{\text{unstabsteer},T_{\text{drivingrisk}}}$	X_3	X_{16}	X_{29}		

mb base connectivity		1	2	3	4	5
X_{30}	$\mathbf{W}_{\text{unfocgaze}, T_{\text{drivingrisk}}}$	X_4	X_{16}	X_{30}		
X_{31}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{drivingrisk}}}$	X_6	X_{16}	X_{31}		
X_{32}	$\mathbf{W}_{\text{exhrisk}, T_{\text{restadvice}}}$	X_5	X_{23}	X_{32}		
X_{33}	$\mathbf{W}_{\text{restadvice}, T_{\text{restadvice}}}$	X_8	X_{23}	X_{33}		
X_{34}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{slowdown}}}$	X_6	X_{24}	X_{34}		
X_{35}	$\mathbf{W}_{\text{driving}, T_{\text{slowdown}}}$	X_7	X_{24}	X_{35}		
X_{36}	$\mathbf{W}_{\text{slowdown}, T_{\text{slowdown}}}$	X_9	X_{24}	X_{36}		
X_{37}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{blockstart}}}$	X_6	X_{25}	X_{37}		
X_{38}	$\mathbf{W}_{\text{driving}, T_{\text{blockstart}}}$	X_7	X_{25}	X_{38}		
X_{39}	$\mathbf{W}_{\text{blockstart}, T_{\text{blockstart}}}$	X_{10}	X_{25}	X_{39}		
X_{40}	$\mathbf{H}_{\mathbf{W}T_{\text{exhrisk}}}$	X_1				
X_{41}	$\mathbf{H}_{\mathbf{W}T_{\text{drivingrisk}}}$	X_2	X_3	X_4		
X_{42}	$\mathbf{H}_{\mathbf{W}T_{\text{restadvice}}}$	X_5				
X_{43}	$\mathbf{H}_{\mathbf{W}T_{\text{slowdown}}}$	X_6	X_7			
X_{44}	$\mathbf{H}_{\mathbf{W}T_{\text{blockstart}}}$	X_6	X_7			

Figure B.1. Role matrices specifying *connectivity* characteristics: **mb** for base connections.

mcw connection weights		1	2	3	4	5
X_1	longdrive	1				
X_2	alcohol	1				
X_3	unstabsteer	1				
X_4	unfocgaze	1				
X_5	exhrisk	X_{11}				
X_6	drivingrisk	X_{12}	X_{13}	X_{14}		
X_7	driving	1				
X_8	restadvice	X_{17}	X_{18}			
X_9	slowdown	X_{19}	X_{20}			
X_{10}	blockstart	X_{21}	X_{22}			
X_{11}	$\mathbf{W}_{\text{longdrive}, \text{exhrisk}}$	1	1	1		
X_{12}	$\mathbf{W}_{\text{alcohol}, \text{drivingrisk}}$	1	1	1		
X_{13}	$\mathbf{W}_{\text{unstabsteer}, \text{drivingrisk}}$	1	1	1		
X_{14}	$\mathbf{W}_{\text{unfocgaze}, \text{drivingrisk}}$	1	1	1		

mcw connection weights		1	2	3	4	5
X_{15}	T_{exhrisk}	X_{26}	X_{27}	0.9		
X_{16}	$T_{\text{drivingrisk}}$	X_{28}	X_{29}	X_{30}	X_{31}	0.9
X_{17}	$W_{\text{exhrisk, restadvice}}$	1	1	1		
X_{18}	$W_{\text{driving, restadvice}}$	1	1	1		
X_{19}	$W_{\text{drivingrisk, slowdown}}$	1	1	1		
X_{20}	$W_{\text{driving, slowdown}}$	1	1	1		
X_{21}	$W_{\text{drivingrisk, blockstart}}$	1	1	1		
X_{22}	$W_{\text{driving, blockstart}}$	1	1	1		
X_{23}	$T_{\text{restadvice}}$	X_{32}	X_{33}	1		
X_{24}	T_{slowdown}	X_{34}	X_{35}	X_{36}	1	
X_{25}	$T_{\text{blockstart}}$	X_{37}	X_{38}	X_{39}	1	
X_{26}	$W_{\text{longdrive, } T_{\text{exhrisk}}}$	1	1	1		
X_{27}	$W_{\text{exhrisk, } T_{\text{exhrisk}}}$	1	1	1		
X_{28}	$W_{\text{alcohol, } T_{\text{drivingrisk}}}$	1	1	1		
X_{29}	$W_{\text{unstabsteer, } T_{\text{drivingrisk}}}$	1	1	1		
X_{30}	$W_{\text{unfocgaze, } T_{\text{drivingrisk}}}$	1	1	1		
X_{31}	$W_{\text{drivingrisk, } T_{\text{drivingrisk}}}$	1	1	1		
X_{32}	$W_{\text{exhrisk, } T_{\text{restadvice}}}$	1	1	1		
X_{33}	$W_{\text{restadvice, } T_{\text{restadvice}}}$	1	1	1		
X_{34}	$W_{\text{drivingrisk, } T_{\text{slowdown}}}$	1	1	1		
X_{35}	$W_{\text{driving, } T_{\text{slowdown}}}$	1	1	1		
X_{36}	$W_{\text{slowdown, } T_{\text{slowdown}}}$	1	1	1		
X_{37}	$W_{\text{drivingrisk, } T_{\text{blockstart}}}$	1	1	1		
X_{38}	$W_{\text{driving, } T_{\text{blockstart}}}$	1	1	1		
X_{39}	$W_{\text{blockstart, } T_{\text{blockstart}}}$	1	1	1		
X_{40}	$H_{WT_{\text{exhrisk}}}$	1				
X_{41}	$H_{WT_{\text{drivingrisk}}}$	1	1	1		
X_{42}	$H_{WT_{\text{restadvice}}}$	1				
X_{43}	$H_{WT_{\text{slowdown}}}$	1	1			
X_{44}	$H_{WT_{\text{blockstart}}}$	1	-1			

Figure B.2. Role matrices specifying *connectivity* characteristics: mcw for connection weights.

Three combination functions are used, the logistic sum combination function **alogistic**, and the Hebbian learning functions **hebb** and **hebbneg** (see Tables 1 and 2). For a general explanation of role matrices, see Appendix A.

mmcfw combination function weights		1 alogistic	2 hebb	3 hebbneg
X_1	longdrive	1		
X_2	alcohol	1		
X_3	unstabsteer	1		
X_4	unfogaze	1		
X_5	exhrisk	1		
X_6	drivingrisk	1		
X_7	driving	1		
X_8	restadvice	1		
X_9	slowdown	1		
X_{10}	blockstart	1		
X_{11}	$W_{\text{longdrive, exhrisk}}$		1	
X_{12}	$W_{\text{alcohol, drivingrisk}}$		1	
X_{13}	$W_{\text{unstabsteer, drivingrisk}}$		1	
X_{14}	$W_{\text{unfogaze, drivingrisk}}$		1	
X_{15}	T_{exhrisk}	1		
X_{16}	$T_{\text{drivingrisk}}$	1		
X_{17}	$W_{\text{exhrisk, restadvice}}$		1	
X_{18}	$W_{\text{driving, restadvice}}$		1	
X_{19}	$W_{\text{drivingrisk, slowdown}}$		1	
X_{20}	$W_{\text{driving, slowdown}}$		1	
X_{21}	$W_{\text{drivingrisk, blockstart}}$		1	
X_{22}	$W_{\text{driving, blockstart}}$			1
X_{23}	$T_{\text{restadvice}}$	1		
X_{24}	T_{slowdown}	1		
X_{25}	$T_{\text{blockstart}}$	1		
X_{26}	$W_{\text{longdrive, } T_{\text{exhrisk}}}$			1
X_{27}	$W_{\text{exhrisk, } T_{\text{exhrisk}}}$		1	
X_{28}	$W_{\text{alcohol, } T_{\text{drivingrisk}}}$			1
X_{29}	$W_{\text{unstabsteer, } T_{\text{drivingrisk}}}$			1

mmcfw combination function weights		1	alogistic	2	hebb	3	hebbneg
X_{30}	$\mathbf{W}_{\text{unfocgaze}, T_{\text{drivingrisk}}}$					1	
X_{31}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{drivingrisk}}}$			1			
X_{32}	$\mathbf{W}_{\text{exhrisk}, T_{\text{restadvice}}}$					1	
X_{33}	$\mathbf{W}_{\text{restadvice}, T_{\text{restadvice}}}$			1			
X_{34}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{slowdown}}}$					1	
X_{35}	$\mathbf{W}_{\text{driving}, T_{\text{slowdown}}}$					1	
X_{36}	$\mathbf{W}_{\text{slowdown}, T_{\text{slowdown}}}$			1			
X_{37}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{blockstart}}}$					1	
X_{38}	$\mathbf{W}_{\text{driving}, T_{\text{blockstart}}}$			1			
X_{39}	$\mathbf{W}_{\text{blockstart}, T_{\text{blockstart}}}$			1			
X_{40}	$\mathbf{H}_{\mathbf{W}T_{\text{exhrisk}}}$	1					
X_{41}	$\mathbf{H}_{\mathbf{W}T_{\text{drivingrisk}}}$	1					
X_{42}	$\mathbf{H}_{\mathbf{W}T_{\text{restadvice}}}$	1					
X_{43}	$\mathbf{H}_{\mathbf{W}T_{\text{slowdown}}}$	1					
X_{44}	$\mathbf{H}_{\mathbf{W}T_{\text{blockstart}}}$	1					

Figure B.3. Role matrices specifying *aggregation* characteristics: **mcfw** for combination function weights.

		1	alogistic	2	hebb	3	hebbneg
		1	2	1	1		
mcfp combination function parameters		n	τ	μ	μ		
X_1	longdrive	8	0.5				
X_2	alcohol	8	0.5				
X_3	unstabsteer	8	0.5				
X_4	unfocgaze	8	0.5				
X_5	exhrisk	8	X_{15}				
X_6	drivingrisk	8	X_{16}				
X_7	driving	8	0.5				
X_8	restadvice	8	X_{23}				
X_9	slowdown	8	X_{24}				
X_{10}	blockstart	8	X_{25}				
X_{11}	$\mathbf{W}_{\text{longdrive}, \text{exhrisk}}$				0.95		
X_{12}	$\mathbf{W}_{\text{alcohol}, \text{drivingrisk}}$				0.95		
X_{13}	$\mathbf{W}_{\text{unstabsteer}, \text{drivingrisk}}$				0.95		
X_{14}	$\mathbf{W}_{\text{unfocgaze}, \text{drivingrisk}}$				0.95		

	1	2	3
	alogistic	hebb	hebbneg
mcfp combination function parameters	1 <i>n</i>	2 τ	1 μ 1 μ
X_{15} T_{exhrisk}	8	0.5	
X_{16} $T_{\text{drivingrisk}}$	8	0.5	
X_{17} $W_{\text{exhrisk, restadvice}}$			0.95
X_{18} $W_{\text{driving, restadvice}}$			0.95
X_{19} $W_{\text{drivingrisk, slowdown}}$			0.95
X_{20} $W_{\text{driving, slowdown}}$			0.95
X_{21} $W_{\text{drivingrisk, blockstart}}$			0.95
X_{22} $W_{\text{driving, blockstart}}$			0.95
X_{23} $T_{\text{restadvice}}$	8	0.5	
X_{24} T_{slowdown}	8	0.2	
X_{25} $T_{\text{blockstart}}$	8	0.5	
X_{26} $W_{\text{longdrive, } T_{\text{exhrisk}}}$			0.95
X_{27} $W_{\text{exhrisk, } T_{\text{exhrisk}}}$			0.95
X_{28} $W_{\text{alcohol, } T_{\text{drivingrisk}}}$			0.95
X_{29} $W_{\text{unstabsteer, } T_{\text{drivingrisk}}}$			0.95
X_{30} $W_{\text{unfocgaze, } T_{\text{drivingrisk}}}$			0.95
X_{31} $W_{\text{drivingrisk, } T_{\text{drivingrisk}}}$			0.95
X_{32} $W_{\text{exhrisk, } T_{\text{restadvice}}}$			0.95
X_{33} $W_{\text{restadvice, } T_{\text{restadvice}}}$			0.95
X_{34} $W_{\text{drivingrisk, } T_{\text{slowdown}}}$			0.95
X_{35} $W_{\text{driving, } T_{\text{slowdown}}}$			0.95
X_{36} $W_{\text{slowdown, } T_{\text{slowdown}}}$			0.95
X_{37} $W_{\text{drivingrisk, } T_{\text{blockstart}}}$			0.95
X_{38} $W_{\text{driving, } T_{\text{blockstart}}}$			0.95
X_{39} $W_{\text{blockstart, } T_{\text{blockstart}}}$			0.95
X_{40} $H_{WT_{\text{exhrisk}}}$	10	0.7	
X_{41} $H_{WT_{\text{drivingrisk}}}$	10	0.7	
X_{42} $H_{WT_{\text{restadvice}}}$	10	0.7	
X_{43} $H_{WT_{\text{slowdown}}}$	10	1.4	
X_{44} $H_{WT_{\text{blockstart}}}$	10	0.7	

Figure B.4. Role matrices specifying *aggregation* characteristics: **mcfp** for combination function parameters.

ms speed factors	1	iv initial values	1
X_1 longdrive	0	X_1 longdrive	0
X_2 alcohol	0	X_2 alcohol	0
X_3 unstabsteer	0	X_3 unstabsteer	0
X_4 unfocgaze	0	X_4 unfocgaze	0
X_5 exhrisk	0.5	X_5 exhrisk	0
X_6 drivingrisk	0.5	X_6 drivingrisk	0
X_7 driving	0	X_7 driving	0
X_8 restadvice	0.5	X_8 restadvice	0
X_9 slowdown	0.5	X_9 slowdown	0
X_{10} blockstart	0.5	X_{10} blockstart	0
X_{11} $\mathbf{W}_{\text{longdrive,exhrisk}}$	X_{40}	X_{11} $\mathbf{W}_{\text{longdrive,exhrisk}}$	0.1
X_{12} $\mathbf{W}_{\text{alcohol,drivingrisk}}$	X_{41}	X_{12} $\mathbf{W}_{\text{alcohol,drivingrisk}}$	0.1
X_{13} $\mathbf{W}_{\text{unstabsteer,drivingrisk}}$	X_{41}	X_{13} $\mathbf{W}_{\text{unstabsteer,drivingrisk}}$	0.1
X_{14} $\mathbf{W}_{\text{unfocgaze,drivingrisk}}$	X_{41}	X_{14} $\mathbf{W}_{\text{unfocgaze,drivingrisk}}$	0.1
X_{15} $\mathbf{T}_{\text{exhrisk}}$	X_{40}	X_{15} $\mathbf{T}_{\text{exhrisk}}$	1
X_{16} $\mathbf{T}_{\text{drivingrisk}}$	X_{41}	X_{16} $\mathbf{T}_{\text{drivingrisk}}$	1
X_{17} $\mathbf{W}_{\text{exhrisk,restadvice}}$	X_{42}	X_{17} $\mathbf{W}_{\text{exhrisk,restadvice}}$	0.1
X_{18} $\mathbf{W}_{\text{driving,restadvice}}$	X_{42}	X_{18} $\mathbf{W}_{\text{driving,restadvice}}$	0.1
X_{19} $\mathbf{W}_{\text{drivingrisk,slowdown}}$	X_{43}	X_{19} $\mathbf{W}_{\text{drivingrisk,slowdown}}$	0.1
X_{20} $\mathbf{W}_{\text{driving,slowdown}}$	X_{43}	X_{20} $\mathbf{W}_{\text{driving,slowdown}}$	0.1
X_{21} $\mathbf{W}_{\text{drivingrisk,blockstart}}$	X_{44}	X_{21} $\mathbf{W}_{\text{drivingrisk,blockstart}}$	0.1
X_{22} $\mathbf{W}_{\text{driving,blockstart}}$	X_{44}	X_{22} $\mathbf{W}_{\text{driving,blockstart}}$	-0.1
X_{23} $\mathbf{T}_{\text{restadvice}}$	X_{42}	X_{23} $\mathbf{T}_{\text{restadvice}}$	1
X_{24} $\mathbf{T}_{\text{slowdown}}$	X_{43}	X_{24} $\mathbf{T}_{\text{slowdown}}$	1
X_{25} $\mathbf{T}_{\text{blockstart}}$	X_{44}	X_{25} $\mathbf{T}_{\text{blockstart}}$	1
X_{26} $\mathbf{W}_{\text{longdrive},\mathbf{T}_{\text{exhrisk}}}$	0.1	X_{26} $\mathbf{W}_{\text{longdrive},\mathbf{T}_{\text{exhrisk}}}$	-0.1
X_{27} $\mathbf{W}_{\text{exhrisk},\mathbf{T}_{\text{exhrisk}}}$	0.1	X_{27} $\mathbf{W}_{\text{exhrisk},\mathbf{T}_{\text{exhrisk}}}$	0.1
X_{28} $\mathbf{W}_{\text{alcohol},\mathbf{T}_{\text{drivingrisk}}}$	0.1	X_{28} $\mathbf{W}_{\text{alcohol},\mathbf{T}_{\text{drivingrisk}}}$	-0.1
X_{29} $\mathbf{W}_{\text{unstabsteer},\mathbf{T}_{\text{drivingrisk}}}$	0.1	X_{29} $\mathbf{W}_{\text{unstabsteer},\mathbf{T}_{\text{drivingrisk}}}$	-0.1
X_{30} $\mathbf{W}_{\text{unfocgaze},\mathbf{T}_{\text{drivingrisk}}}$	0.1	X_{30} $\mathbf{W}_{\text{unfocgaze},\mathbf{T}_{\text{drivingrisk}}}$	-1
X_{31} $\mathbf{W}_{\text{drivingrisk},\mathbf{T}_{\text{drivingrisk}}}$	0.1	X_{31} $\mathbf{W}_{\text{drivingrisk},\mathbf{T}_{\text{drivingrisk}}}$	0.1

ms speed factors		1	iv initial values		1
X_{32}	$\mathbf{W}_{\text{exhrisk}, T_{\text{restadvice}}}$	0.1	X_{32}	$\mathbf{W}_{\text{exhrisk}, T_{\text{restadvice}}}$	-1
X_{33}	$\mathbf{W}_{\text{restadvice}, T_{\text{restadvice}}}$	0.1	X_{33}	$\mathbf{W}_{\text{restadvice}, T_{\text{restadvice}}}$	0.1
X_{34}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{slowdown}}}$	0.1	X_{34}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{slowdown}}}$	-1
X_{35}	$\mathbf{W}_{\text{driving}, T_{\text{slowdown}}}$	0.1	X_{35}	$\mathbf{W}_{\text{driving}, T_{\text{slowdown}}}$	-1
X_{36}	$\mathbf{W}_{\text{slowdown}, T_{\text{slowdown}}}$	0.1	X_{36}	$\mathbf{W}_{\text{slowdown}, T_{\text{slowdown}}}$	0.1
X_{37}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{blockstart}}}$	0.1	X_{37}	$\mathbf{W}_{\text{drivingrisk}, T_{\text{blockstart}}}$	-1
X_{38}	$\mathbf{W}_{\text{driving}, T_{\text{blockstart}}}$	0.1	X_{38}	$\mathbf{W}_{\text{driving}, T_{\text{blockstart}}}$	0.1
X_{39}	$\mathbf{W}_{\text{blockstart}, T_{\text{blockstart}}}$	0.1	X_{39}	$\mathbf{W}_{\text{blockstart}, T_{\text{blockstart}}}$	0.1
X_{40}	$\mathbf{H}_{\mathbf{W}T_{\text{exhrisk}}}$	0.05	X_{40}	$\mathbf{H}_{\mathbf{W}T_{\text{exhrisk}}}$	0
X_{41}	$\mathbf{H}_{\mathbf{W}T_{\text{drivingrisk}}}$	0.05	X_{41}	$\mathbf{H}_{\mathbf{W}T_{\text{drivingrisk}}}$	0
X_{42}	$\mathbf{H}_{\mathbf{W}T_{\text{restadvice}}}$	0.05	X_{42}	$\mathbf{H}_{\mathbf{W}T_{\text{restadvice}}}$	0
X_{43}	$\mathbf{H}_{\mathbf{W}T_{\text{slowdown}}}$	0.05	X_{43}	$\mathbf{H}_{\mathbf{W}T_{\text{slowdown}}}$	0
X_{44}	$\mathbf{H}_{\mathbf{W}T_{\text{blockstart}}}$	0.05	X_{44}	$\mathbf{H}_{\mathbf{W}T_{\text{blockstart}}}$	0

Figure B.5. Role matrix **ms** specifying *timing* characteristics and vector **iv** of initial values.