A Second-Order Adaptive Network Model for Learner-Controlled Mental Model Learning Processes

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Abstract. Learning new knowledge or a new skill usually requires the development of an adequate internal mental model in the form of a mental network. The learning process for such an internal model involves (first-order) mental network adaptation. Such a learning process often integrates different elements, such as learning by observation and learning by instruction. For an effective learning process, a main issue is to get an appropriate timing of the different elements. To control the timing of these elements of a learning process, the mental network adaptation process has to be adaptive itself: second-order mental network adaptation. The second-order adaptive mental network model proposed here addresses this, where the first-order adaptation process models the learning process of mental network models and the second-order adaptation process controls the timing of the elements of the learning process. It is illustrated for learner-controlled mental model learning in the context of driving a car where the learner is in control of the integration of learning by observation and learning by instruction.

1 Introduction

For cognitive functioning, usually mental models are applied for learning and problem solving of individuals in interaction with their environment; e.g., [5–7, 10, 12, 19, 20, 22, 24, 30, 31, 33–37]. As an example, mental models of devices are applied to be able to use these devices; e.g., [11, 21]. The question how mental models are developed or learnt and how to control such learning processes is an interesting and challenging one, and computational models of such processes are almost absent; e.g., [3, 8, 14]. As one of the rare exceptions, in [8] a production rule modeling format is used to simulate students' construction of energy models in physics. In general, however, research into how mental models develop especially for learning to operate a device, is hard to find.

The current paper contributes such a computational model based on multi-order adaptive network-oriented modeling [40] and illustrated for learner-controlled mental model development while learning to drive a car. Such a driver's mental model and how it can be developed in an effective manner can be a basis for the design of virtual pedagogical agents, and for support of the interaction between driver and the adaptive automation in cars.

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Network-oriented modeling for adaptive networks [40] can be applied in general to model adaptive mental processes as interactions of mental states where their connections change based on principles of network adaptation such as Hebbian learning [16]. Learning of mental models in particular involves adaptation of these connections, but also control of this learning, which is a form of second-order adaptation. The network-oriented modeling approach from [38–40] covers such multi-order adaptive processes.

So, as a mental model can be modeled as a base network, learning it can be modeled as (first-order) adaptation of that base network. Moreover, the control of such learning processes can be modeled as a form of second-order adaptation, which adapts the first-order adaptation. Thus, the three-level second-order adaptive network architecture for mental model development was obtained which is presented in the current paper. It is illustrated for learning mental models by a learner-controlled combination of observational and instructional learning in the context of learning how a car works and how to drive it.

First, a brief literature overview can be found in Sect. 2. In Sect. 3, the overall design of the developed second-order adaptive network architecture is discussed, covering integration of observational and instructional learning and its control. In Sect. 4, a more detailed refinement of this general architecture is discussed to address the case study involving learner-controlled integration of observational and instructional learning. Simulations for the example scenario are discussed in Sect. 5. Section 6 is a final discussion.

2 A Brief Overview of Background Knowledge

The notion of (internal) mental model has a longstanding tradition in Cognitive and Social Sciences and in Educational Sciences; e.g., [2, 5–7, 10, 12, 19, 20, 22–31, 33–37, 46]. Within educational psychology the notion model-based learning indicates learning that occurs when people construct coherent mental models [4, 5, 9, 15, 24]. Buckley [5] formulates it as: 'Model-based learning is a dynamic, recursive process of learning by building mental models.' [5], p. 896. More specifically, the following elements can be considered in such learning.

Learning by observation or *observational learning* takes place when observation and/or imitation of others is one of the sources that help the formation of mental models. In model-centered learning, trainees watch someone else perform a target behavior and then attempt to reenact it; e.g., [4, 44]. Demonstration is an often used method in teaching new motor tasks. This particular type of learning is referred to as observational motor learning. Empirical findings show that observational motor learning improves action perception and motor execution. Mirror neurons are assumed to be responsible for the ability to learn by observing and/or imitating others as they help us understand the actions performed by others; e.g., [18, 32, 41].

Learning by instruction or *instructional learning* assumes that instructions from an expert instructor can be helpful. For a beginner, learning by discovery or observation may involve a great deal of trial and error; e.g., [35, 36]. Hence, along with self-learning, instructions from an expert are considered useful to build accurate and effective mental models. This notion is supported by scaffolded model-based learning in which a variety of supports like prompts, questions, hints, stories, conceptual models, visualizations are provided to assist the students' progress during learning tasks; e.g., [17].

Learner-controlled learning for the integration of observational and instructional learning is discussed by Gibbons and Gray [13], thereby putting forward that instructions serve human learning processes best when under the control of the learner. Thus instructions do not cause learning but rather support it. The scaffolded model-based learning mentioned above supports this integration. Kozma [23] suggested that individuals do use external information sources for model construction provided in specific learning environments. Learners are sensitive to characteristics of the learning environment like availability of certain information at a given time, the structure of information and how it is introduced as well as the ease with which it can be accessed. Thus, the learner's need for instruction and ease for acquiring it are crucial for development of accurate mental models. In guided discovery methods of learning, the learner seeks for information in the environment in order to complete the initial mental model or prior understanding. It requires the learner to be proactive and direct the learning experience. However, in expository teaching methods, an instructor directs the mental model progression by providing adequate information [29]. Meela, and Yuenyong [25] demonstrated in their study that Model-Based Inquiry (MBI) could support a student's mental model in scientific learning. MBI focuses on developing students' formulations of questions and procedures, creating and communicating conclusions consistent with empirical evidence [27]. Knowledge of results or feedback on performance are a significant factor in learning [1]. Many studies have established that feedback is crucial in skill acquisition [43].

Thus, in the *adaptive network model* introduced below, it was modeled that the learner can seek for instructions whenever it may be needed or as a feedback about what she/he has learnt by observation. This was addressed by utilizing *control states* for instructions on a separate level within the adaptive network model by which the learner controls the amount and timing of incoming information by seeking it only when it seems appropriate to her/him. More specifically, based on the above literature, in next section it is discussed how a learning process based on mental models can be modeled by a three-level adaptive network model. Applying a network-oriented modeling perspective for adaptive networks [40], the above literature leads to the following three different description levels that have to be addressed. First of all, the mental models themselves can be described by base networks. Next, during learning, the mental models change; this change of mental models can be described by (first-order) network adaptation. Finally, control of such a learning process is a form of adaptation of the learning process; this can be described by adaptation of the first-order adaptive network for the learning process, which is called *second-order network adaptation.*

3 Network Architecture for Controlled Mental Model Learning

In this section a global view on the architecture of the introduced network model for learner-controlled mental model learning is discussed. In accordance with what was concluded in Sect. 2, this architecture has to cover the following three types of processes in an integrated manner: (1) The mental models themselves described by networks, (2) Learning as change of mental models described by first-order network adaptation, and (3) Control of learning processes described by second-order network adaptation. Using the notion of multi-level network reification [38–40], these three description levels indeed can be modeled adequately by a three-level second-order adaptive network architecture as depicted in Fig. 1.

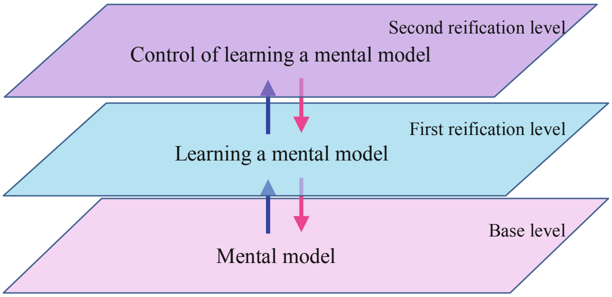

Fig. 1. Overview of the introduced second-order adaptive network architecture

Here, for any specific application each plane contains a specific network and specific upward and downward connections define the interactions between the different levels. The more specific adaptive network model described in Sect. 4 will be such a refinement of this overall network architecture. The generic types of states and connections used at and between the three levels within this architecture are shown in Tables 1 and 2. Note that the colours used in these tables indicate to which level the states belong, as they correspond to the colours of the planes in Figs. 1, 2 and 3. At the base level, the learner's (subjective) mental model is defined by the connections (between base states) $\mathbf{BS}_X \rightarrow \mathbf{BS}_Y$, whereas the connections (between observation states) $\mathbf{OS}_X \rightarrow \mathbf{OS}_Y$ define the (objective) relations in the real world. Moreover, the connections (from observation state to base state) $\mathbf{OS}_Y \rightarrow \mathbf{BS}_Y$ define the mirroring process by which the observations affect the learner's own states.

At the first reification level, the connections $\mathbf{LW}_{X,Y} \rightarrow \mathbf{RW}_{X,Y}$ and $\mathbf{IW}_{X,Y} \rightarrow \mathbf{RW}_{X,Y}$ model the integration of what is learnt by observational learning and by instructional learning, respectively. The connections $\mathbf{IS}_{X,Y} \rightarrow \mathbf{IW}_{X,Y}$ model the instruction communication actions from instructor to learner. The effect of activation of second-order state $\mathbf{CIW}_{X,Y}$ is that the connection (or channel) from the instructor info state $\mathbf{IS}_{X,Y}$ to state $\mathbf{IW}_{X,Y}$ of the learner is opened (i.e., gets high connection weight) so that this information is transferred from instructor state $\mathbf{IS}_{X,Y}$ to learner state $\mathbf{IW}_{X,Y}$.This opening of the channel $\mathbf{IS}_{X,Y} \rightarrow \mathbf{IW}_{X,Y}$ is modeled by the connections $\mathbf{CIW}_{X,Y} \rightarrow \mathbf{IW}_{X,Y}$, where $\mathbf{CIW}_{X,Y}$ represents the role of connection weight from $\mathbf{IS}_{X,Y}$ to $\mathbf{IW}_{X,Y}$. Via its incoming observational learning monitoring connection $\mathbf{LW}_{X,Y} \rightarrow \mathbf{CIW}_{X,Y,}$ the control state $\mathbf{CIW}_{X,Y}$ will become active depending on the corresponding **LW**-state $\mathbf{LW}_{X,Y}$. This models asking the instructor for verification and confirmation of what was just learnt by observation.

A more detailed display of the network's connectivity for a specific case study can be found in Sect. 4, Figs. 2 and 3.

Table 1. Types of states in the introduced three level network architecture

BS_Y	Base states for the considered mental model of the learner
$\mathbf{OS}_Y$	The corresponding observation states in the real world
$\mathbf{IS}_{X,Y}$	Representation for the connection weights of the mental model of the instructor
$\mathbf{LW}_{X,Y}$	Representation for the connection weights for the mental model as learnt from observation (using the Hebbian learning principle)
$\mathbf{IW}_{X,Y}$	Representation for the connection weights for the mental model as learnt from instruction (using the instructor)
$\mathbf{RW}_{X,Y}$	Representation for the connection weights for the learner's mental model integrating observational (via $\mathbf{LW}_{X,Y}$) and instructional (via $\mathbf{IW}_{X,Y}$) learning
$\mathbf{CIW}_{X,Y}$	Initiation of instruction: control state for requesting the weight of the connection from X to Y for the mental model from the instructor

Table 2. Types of connections in the introduced adaptive network architecture

Intra-level connections		
$\mathbf{BS}_X \rightarrow \mathbf{BS}_Y$	The learner's (subjective) connections between the base states, indicating the current mental model of the learner	
$\mathbf{OS}_X \rightarrow \mathbf{OS}_Y$	The real world's (objective) connections between the observation states, indicating the real-world process	
$\mathbf{OS}_Y \rightarrow \mathbf{BS}_Y$	Mirroring connections defining the mirroring process for the base states. These connections model the effect of observations on the learner.	
$\mathbf{IS}_{X,Y} \rightarrow \mathbf{IW}_{X,Y}$	Being informed by the instructor: the communicated instruction concerning the connection from X to Y. These connections $\mathbf{IS}_{X,Y} \rightarrow \mathbf{IW}_{X,Y}$ can be controlled by control states $\mathbf{CIW}_{X,Y}$ at the second reification level	
$\mathbf{IW}_{X,Y} \rightarrow \mathbf{RW}_{X,Y}$	Integration of knowledge obtained by instructional learning	
$\mathbf{LW}_{X,Y} \rightarrow \mathbf{RW}_{X,Y}$	Integration of knowledge obtained by observational learning	
Interlevel connections		
$\mathbf{BS}_X \rightarrow \mathbf{LW}_{X,Y}$ $\mathbf{BS}_Y \rightarrow \mathbf{LW}_{X,Y}$	Connections supporting observational learning	Upward from base level to first reification level
$\mathbf{RW}_{X,Y} \rightarrow \mathbf{BS}_Y$	Effectuation of base connection weights in the mental model	Downward from first reification level to base level
$\mathbf{LW}_{X,Y} \rightarrow \mathbf{CIW}_{X,Y}$	Observational learning monitoring connections	Upward from first to second reification level
$\mathbf{CIW}_{X,Y} \rightarrow \mathbf{IW}_{X,Y}$	Effectuation of instructional learning control	Downward from second to first reification level

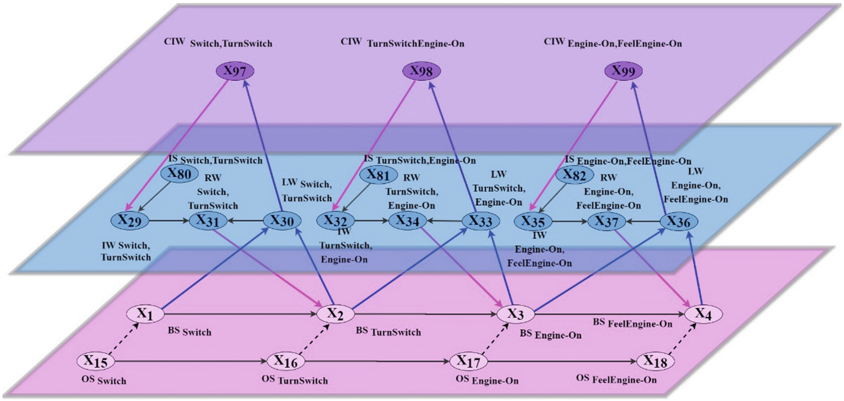

Fig. 2. Connectivity for part of the second-order adaptive network model.

4 Detailed Description of the Second-Order Adaptive Network Model for a Case Study

In this section, a more detailed description is presented of the designed second-order adaptive network model applied to an illustrative case study, based on the following scenario:

> Person A has almost no knowledge about a car's components, and their interactions and how to drive a car. This person's mental model of the car and driving it has to be learned during driving lessons. During person A's first driving lesson, instructor B demonstrates how to start a car and get it moving. The observation of B makes that A learns an initial mental model of the car and operating it (observational learning). During A's further learning, an iterative process of extending and/or

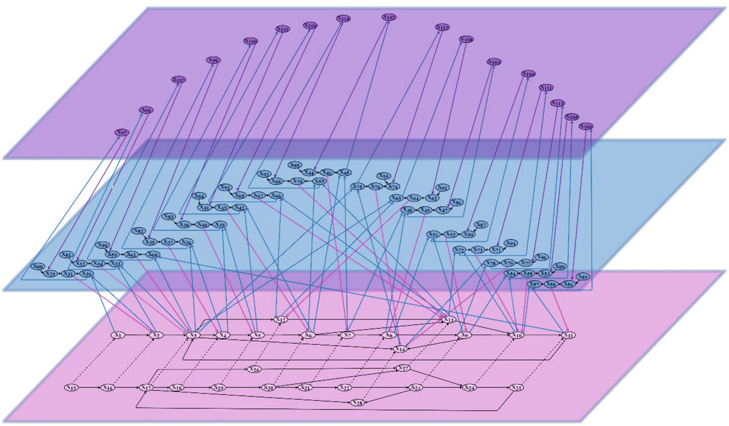

Fig. 3. Connectivity for the complete adaptive network model.

modifying the mental model takes place, leading to a more accurate and complete mental model. Besides observational learning, also learning from instruction plays an important role (instructional learning). This instructional learning takes place by incorporating incoming information communicated by B. In this scenario this instructional learning only takes place upon request of the learner (learner-controlled instructional learning), as a form of verification and consolidation after A learnt about it by observational learning.

The network-oriented modeling approach for adaptive networks used here can be found in [38–40]. The characteristics used to describe networks are (for nodes or states X and Y): for *connectivity* connection weights $\boldsymbol{\omega}_{X,Y}$, for *aggregation* combination functions $\mathbf{c}_Y(..)$ and for *timing* speed factors $\boldsymbol{\eta}_Y$. For adaptive networks the notion of *network reification* is used, as has been worked out in detail in [40]. This can be done iteratively to obtain multiple orders of adaptation and is applied in the way that for each state Y of the base network, for its adaptive network characteristics $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$,$\boldsymbol{\eta}_Y$, additional network states (called *reification states* or *self-model states*) are introduced as new nodes in the network. For example, for adaptive connectivity characteristics, states $\mathbf{RW}_{X,Y}$ are added representing adaptive connection weights $\boldsymbol{\omega}_{X,Y}$. They form a *self-model* of the network's own structure in the form of a subnetwork within the network. To graphically distinguish them from states at the level of X and Y, these reification or self-model states are depicted at one level higher (e.g., see the blue planes in Figs. 1, 2 and 3 with representations of weights of adaptive connections from the base planes).

As in this case the learning is controlled, it is adaptive itself, which is depicted by the third level (purple plane) for *second-order adaptation* in Figs. 1, 2 and 3, which include *second-order reification states* $\mathbf{CIW}_{X,Y}$ that represent the weight of the connection $\mathbf{IS}_{X,Y} \rightarrow \mathbf{IW}_{X,Y}$ of the middle level (see Sect. 3). In accordance with the distinction between different levels discussed above, the designed adaptive network model indeed has three levels as already depicted in Fig. 1: base level (mental model), first reification level (learning of a mental model) and second reification level (controlling learning of a mental model). Each level is graphically depicted in 3D by one horizontal plane (see Figs. 2 and 3). In these figures, the lower (pink) plane contains the base network for the mental model, whereas the middle (blue) plane represents the reification states: the **IS**-States, **IW**-states, **LW**-states, and **RW**-states, all referring to connections between the **BS**-states at the base level. This first reification level enables adaptation of the connections of the mental model; as discussed in Sect. 2, this is needed for learning a mental model. The structure by the lowest two (interacting) levels distinguish the two types of processes (and their interaction): *using* the mental model by changing the **BS**-states represented at the base level (used for *internal simulation* of the mental model) versus *adjusting* the mental model by changing the representations at the reification level of its connections (*adaptation*, *learning* of the mental model). The different types of states are explained in Tables 1, 3, 4. Figure 2 depicts the connectivity for only a part for a small number of the states to support better understanding. The connectivity for the complete network model is shown in Fig. 3. The second reification level (purple plane) enables to control the learning process by changing some of their intra-level connections within the first reification level (which affects the dynamics of these first-order states), based on the second-level reification **CIW**-states (control states); this is used to model *learner-controlled instruction.*

Table 3. Explanation of the base level states in the network model for the case study

States	Explanation	
X_1	BS_{Switch}	Learner's Representation State for Switch
X_2	$BS_{TurnSwitch}$	Learner's Representation State for TurnSwitch
X_3	$BS_{Engine\text{-}On}$	Learner's Representation State for Engine-On
X_4	$BS_{FeelEngine\text{-}On}$	Learner's Representation State for FeelEngine-On
X_5	$BS_{PresClutch}$	Learner's Representation State for PressClutch
X_6	$BS_{Clutch\text{-}On}$	Learner's Representation State for Clutch-On
X_7	$BS_{Gearbox\text{-}Neutral}$	Learner's Representation State for Gearbox-Neutral
X_8	$BS_{PressGear\ 1}$	Learner's Representation State for PressGear1
X_9	$BS_{Gear1\text{-}On}$	Learner's Representation State for Gear1-On
X_{10}	$BS_{PressAccelerator}$	Learner's Representation State for PressAccelerator
X_{11}	$BS_{Accelerator\text{-}On}$	Learner's Representation State for Accelerator-On
X_{12}	$BS_{RevMeter\text{-}On}$	Learner's Representation State for Rev-Meter-On
X_{13}	$BS_{BiteState}$	Learner's Representation State for BiteState
X_{14}	$BS_{MovingState}$	Learner's Representation State for MovingState
X_{15}	OS_{Switch}	Observation State for Switch
……		
X_{28}	$OS_{MovingState}$	Observation State for MovingState

The conceptual representation of a temporal–causal network model like the one mentioned above can easily be transformed in an automated manner into a numerical representation using a dedicated modeling environment; this results in difference or differential equations ([40], Chapter 9):

$$
\begin{aligned}
Y(t+\Delta t) =& Y(t) + \eta_Y\left[\mathbf{aggimpact}_Y(t) - Y(t)\right]\Delta t \\
\text{or } \mathrm{d}Y(t)/\mathrm{d}t =& \eta_Y\left[\mathbf{aggimpact}_Y(t) - Y(t)\right]
\end{aligned}
\tag{1}
$$

where $\mathbf{aggimpact}_Y(t) = \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t))$

In the model presented here, for the states, the following combination functions were used, all generating values in [0, 1] (assuming that their argements are in [0, 1]). The *Euclidean combination function* $\mathbf{eucl}_{\boldsymbol{n},\boldsymbol{\lambda}}(V_1, \ldots, V_k)$ where $\boldsymbol{n}$ is the order (which can be any positive real number), and $\boldsymbol{\lambda}$ the scaling factor is defined by:

$$\mathbf{eucl}_{n,\lambda}(V_1,\ \ldots,\ V_k) = \lambda \tag{2}$$

Table 4. Explanation of reification level states in the network model for the case study

States		Explanation
X_{29}	$IW_{Switch,TurnSwitch}$	Representation state for Informed Weight for Switch → TurnSwitch
X_{30}	$LW_{Switch,TurnSwitch}$	Representation state for Learnt Weight for Switch → TurnSwitch
X_{31}	$RW_{Switch,TurnSwitch}$	Representation state for overall Representative Weight for Switch → TurnSwitch
X_{32}	$IW_{TurnSwitch,Engine\text{-}On}$	Representation state for Informed Weight for TurnSwitch → Engine-On
X_{33}	$LW_{TurnSwitch,Engine\text{-}On}$	Representation state for Learnt Weight for TurnSwitch → Engine-On
X_{34}	$RW_{TurnSwitch,Engine\text{-}On}$	Representation state for Representative Weight for TurnSwitch → Engine-On
X_{35}	$IW_{Engine\text{-}On,FeelEngine\text{-}On}$	Representation state for Informed Weight for Engine-On → FeelEngine-On
X_{36}	$LW_{Engine\text{-}On,FeelEngine\text{-}On}$	Representation state for Learnt Weight for Engine-On → FeelEngine-On
X_{37}	$RW_{Engine\text{-}On,FeelEngine\text{-}On}$	Representation state for Representative Weight for Engine-On → FeelEngine-On
……		
X_{86}	$IS_{Switch,TurnSwitch}$	Representation state for Information State for Switch → TurnSwitch
X_{87}	$IS_{TurnSwitch,Engine\text{-}On}$	Representation state for Information State for TurnSwitch → Engine-On
X_{88}	$IS_{Engine\text{-}On,FeelEngine\text{-}On}$	Representation state for Information State for Engine-On → FeelEngine-On
……		
X_{97}	$CIW_{Switch,TurnSwitch}$	Representation state for control of instruction for Switch → TurnSwitch
X_{98}	$CIW_{TurnSwitch,EngineOn}$	Representation state for control of instruction for TurnSwitch → EngineOn
X_{99}	$CIW_{EngineOn,FeelEngineOn}$	Representation state for control of instruction for Engine-On → FeelEngineOn
……		

where V_1, …, $V_k \in [0, 1]$ indicate the impacts $\boldsymbol{\omega}_{X_i,Y}X_i(t)$ from the states X_1, …, X_k from which Y has an incoming connection. The *Advanced logistic sum combination function* $\mathbf{alogistic}_{\sigma,\tau}(\ldots)$ is used with steepness $\boldsymbol{\sigma}$ and threshold $\boldsymbol{\tau}$ is defined by (with similar V_1,

..., V_k as above):

$$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k) = \left[\frac{1}{1+e^{-\sigma(V_1+\ldots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau})}\right]\left(1+e^{-\sigma\tau}\right) \quad (3)$$

The *Hebbian learning combination function* $\mathbf{hebb}_{\mu}(..)$ for learning of the connection from state X to state Y used in particular for the **LW**-states is defined by

$$\mathbf{hebb}_{\mu}(V_1, V_2, W) = V_1 V_2(1-W) + \mu W \quad (4)$$

where μ is the persistence parameter, V_1 stands for state value $X(t)$, V_2 for $Y(t)$, and W for the learnt connection weight reification state value $\mathbf{LW}_{X,Y}(t)$. A more detailed specification in terms of role matrices can be found in [46].

5 Example Simulation Scenario

The computational network model was simulated using the dedicated software environment implemented in Matlab as described in [40], Ch 9, to study the development of a mental model for a car's functioning and driving it; see Figs. 4, 5, 6 and 7. For the simulation $\Delta t = 0.5$ was chosen, the total time 800 (so 1600 simulation steps); the time scale is left abstract here, for example, it could be seconds. The speed factor for the **BS**-states were set at 0.4, for **OS**-states at 0.05, for **IW**-states at 0.1, and for **LW**-states and **RW**-states at 0.4. For the second-order **CIW**-states the speed factor was set at 0.4. The connection weights between the states and the other characteristics of the network model and the initial values are shown in [46]. For example, all **BS**- and **OS**-states use either the euclidean function or the logistic sum function, all **LW**-states the Hebbian learning function, the **IW**-states the logistic sum function, the **RW**-states the first-order euclidean function, and the **CIW**-states the logistic sum function. All **BS**-states have initial value 0. All **OS**-States have initial value 0, except the first **OS**-State X_{15} which has an initial value of 1. For all the **IW**-, **LW**-, and **RW**- states, the initial value was set at 0.1.

The **IS**-states have constant value 1, as they refer to the knowledge of the instructor (see also Fig. 5). Note that it has been specified in such a way that only one of the **IW**-state or **LW**-state is not enough to get an **RW**-state with a high value close to 1. A typical pattern is that first, based on a learnt **LW**-state only, the **RW**-state gets a value somewhere in the middle of the 0–1 interval, and only after instructional learning making the **IW**-state high, the **RW**-state value increases to a high value close to 1.

The typical pattern is that first based on the value of **LW**-state (i.e., by observational learning), the second-order **CIW**-state is activated (Fig. 6) which in turn makes the **IW**-state getting a value close to 1 (Fig. 7). The **RW**-state gets a value somewhere in the middle of the 0–1 interval, and only after the learner seeks instructional information (or feedback) making the **IW**-state high, the **RW**-state value increases to 1. This shows that the learner actively engages seeking more information to confirm the accuracy of what he/she has learnt by observation. The learner hence controls the amount of information (s)he needs in addition to complete her/his learning based on her/his current level of

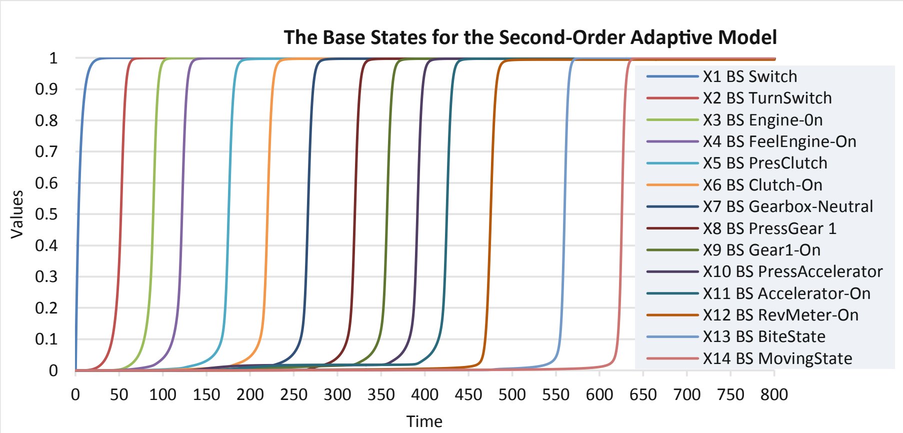

Fig. 4. Dynamics of the Base States X_1-X_{14} showing internal simulation of the mental model.

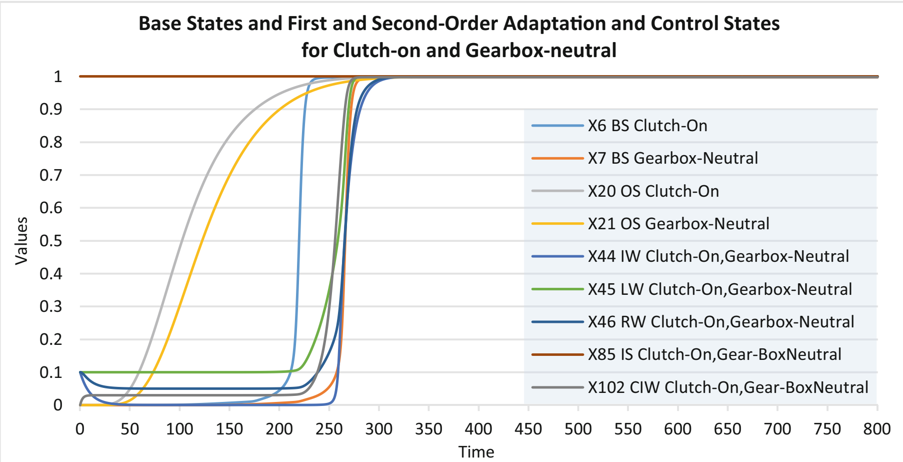

Fig. 5. Base States X_6 (Clutch-on) and X_7 (Gearbox-neutral) with impact from **OS**-states X_{20}, X_{21} and **LW**-state X_{45}, **RW**-state X_{46} and learner **IW**-state X_{44} and instructor **IS**-state X_{85} with control by **CIW**-state X_{102}

understanding by own observation. See also Sect. 3. The results indicated in Fig. 5 display the connection between two **BS**-states X_6 and X_7. Here it can be seen that, together with the value of X_6 becoming 1 at time 210, the **OS**-state X_{21} affects the value of X_7 together with **RW**-state X_{46} which combines the weights of the related **LW**-and **IW**-states. The **CIW**-state controls the weight of **IW**-state according to the **LW**-state's weight.

The state X_7 reaches value 1 at time 250 by an S-curve. The **IS**-state representing knowledge of the instructor remains at 1 all the time (a knowledgeable instructor).

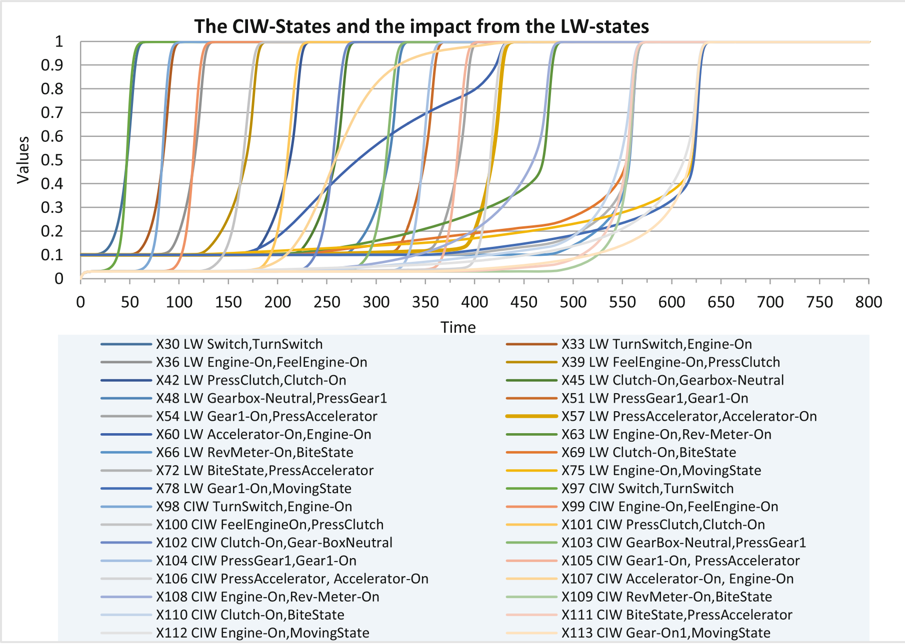

Fig. 6. All control **CIW**-states showing impact from the corresponding observational learning **LW**-states

As a form of evaluation, in Figs. 6 and 7 it is displayed how the activation of each **CIW**-state follows the activation of the corresponding **LW**-state, and how in turn the activation of the **CIW**-state is followed by the corresponding **IW**-state. This confirms that the model displays the intended behavior that first observational learning takes place, after which there is a learner initiative to request corresponding instruction, and appropriate instructional learning indeed takes place after that.

6 Discussion

In the present paper, controlled learning of mental models was explored. The learning usually integrates different types, such as observational learning and instructional learning. For an effective learning process, appropriate timing of the different types of learning is crucial. To control this timing, the mental network adaptation process itself has to be modeled in an adaptive manner as well. The proposed second-order adaptive mental network model addresses this, where the first-order adaptation process models the learning process of a mental network model and the second-order adaptation process controls the focus and timing of the types of learning.

It was illustrated for a case study of learner-controlled mental model learning in the context of a car and driving it, where the learner is in control of the integration of observational learning and instructional learning. Based on the implemented second-order adaptive network model, the learner-controlled learning of mental models while

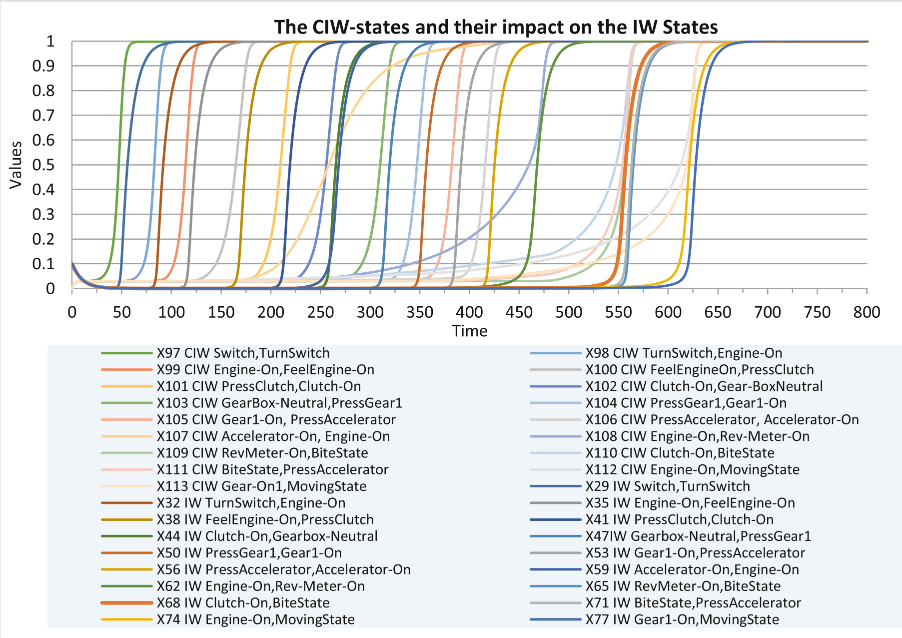

Fig. 7. All control **CIW**-states showing their impact on the corresponding instructional learning **IW**-states

learning about a car and how to drive it based on literature was simulated and shown to work as expected from the literature.

Much literature exists which describes the learning of mental models and is mentioned in the paper. But, formalized computational models for it are very rare; exceptions are [3, 8, 34, 42]. In [8] a production rule modeling format is used to simulate students' construction of energy models in physics and in [34] the PDP modeling format was used to model mental models. In [42] a relatively simple adaptive God model was described, and in [3] the focus is on learning to drive a car. However, in all four cases [3, 8, 34, 42] no second-order adaptive network model is obtained, so there is no control of the learning processes. That is a main difference with the current paper, where the focus is on the control and this is fully addressed by designing a second-order adaptive mental network model. Note, however, the following disclaimer: the literature on mental models is extremely diverse, so there cannot be a claim that the way in which mental models are formalised here from a causality perspective, would be the best formalisation for all of the wide variety of suggested forms of mental models.

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46. Appendix with a full specification of the model. https://www.researchgate.net/publication/343600180