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published in
Complex Networks and Their Applications X
2022

DOI (link to publisher)
10.1007/978-3-030-93409-5_35

document version
Publisher's PDF, also known as Version of record

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Context-Sensitive Mental Model Aggregation in a Second-Order Adaptive Network Model for Organisational Learning

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Abstract. Organisational learning processes often exploit developed individual mental models in order to obtain shared mental models for the organisation by some form of unification or aggregation. The focus in this paper is on this aggregation process, which may depend on a number of contextual factors. It is shown how a second-order adaptive network model for organisation learning can be used to model this process of aggregation of individual mental models in a context-dependent manner.

1 Introduction

Organisational learning is an important but complex adaptive phenomenon within an organisation. It involves a cyclical interplay of different adaptation processes such as individual learning and development of mental models, formation of shared mental models for teams or for the organisation as a whole, and improving individual mental models or team mental models based on a shared mental model of the organisation; e.g., (Argyris and Schön 1978; Bogenrieder 2002; Crossan et al. 1999; Fischhof and Johnson 1997; Kim 1993; McShane and Glinow 2010; Stelmaszczyk 2016; Wiewiora et al. 2019). For example, Kim (1993), p. 44 puts forward that 'Organizational learning is dependent on individuals improving their mental models; making those mental models explicit is crucial to developing new shared mental models'. One of the fundamental issues here is how exactly shared mental models are formed based on developed mental models and, in particular, how that depends on a specific context.

It the past years, it has been found out how self-modeling networks provide an adequate modeling approach to obtain computational models addressing mental models and how they are used for internal simulation, adapted by learning, revision or forgetting, and the control of all this; e.g., (Treur et al. 2022). In recent research, it has also been shown for a relatively simple scenario how this modeling perspective can be exploited to obtain computational models of organisational learning (Canbaloğlu et al. 2021). However, the important issue of how exactly shared mental models are formed

R. M. Benito et al. (Eds.): COMPLEX NETWORKS 2021, SCI 1072, pp. 411–423, 2022.
https://doi.org/10.1007/978-3-030-93409-5_35

in a context-dependent manner based on individual mental models has not been addressed there.

The current paper introduces a computational self-modeling network model for organisational learning with a main focus on this context-dependent formation process of shared mental models based on aggregation of individual mental models. In Sect. 2 some background knowledge for this will briefly be discussed. Section 3 briefly describes the modeling approach based on self-modeling networks used. In Sect. 4, the computational self-modeling network model for organisational learning based on context-dependent aggregation will be introduced. This model will be illustrated by an example simulation scenario in Sect. 5. Finally, Sect. 6 is a discussion section.

2 Background Literature

In this section, some of the multidisciplinary literature about the concepts and processes that need to be addressed are briefly discussed. This provides a basis for the self-modeling network model that will be presented in Sect. 4 and for the scientific justification of the model.

For the history of the *mental model* area, often Kenneth Craik is mentioned as a central person. In his book Craik (1943) describes a mental model as a *small-scale model* that is carried by an organism within its head and based on that the organism 'is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it.' (Craik 1943, p. 61). Shih and Alessi (1993, p. 157) explain that 'By a mental model we mean a person's understanding of the environment. It can represent different states of the problem and the causal relationships among states.' In (Van et al. 2021), an analysis of various types of mental models and the types of mental processes processing are reviewed. Based on this analysis a three-level cognitive architecture has been introduced where:

- the base level models *internal simulation* of a mental model
- the middle level models the *adaptation* of the mental model (formation, learning, revising, and forgetting a mental model, for example)
- the upper-level models the (metacognitive) *control* over these processes

By using the notion of self-modeling network (or reified network) from (Treur 2020a; Treur 2020b), recently this cognitive architecture has been formalized computationally and used in computer simulations for various applications of mental models; for an overview of this approach and its applications, see (Treur et al. 2022).

Mental models also play an important role when people work together in teams. When every team member has a different individual mental model of the task that is performed, then this will stand in the way of good teamwork. Therefore, ideally these mental models should be aligned to such an extent that it becomes one *shared mental model* for all team members. Examples of computational models of a shared mental model and how imperfections in it work out can be found in (Van Ments et al. 2021a; Van Ments et al. 2021b).

Organisational learning is an area which has received much attention over time; see, for example, (Argyris and Schön 1978; Bogenrieder 2002; Crossan et al. 1999; Fischhof and Johnson 1997; Kim, 1993; McShane and Glinow 2010; Stelmaszczyk 2016; Wiewiora et al. 2019). However, contributions to computational formalization of organisational learning are very rare. By Kim (1993), mental models are considered a vehicle for both individual learning and organizational learning. By learning and developing individual mental models, a basis for formation of shared mental models for the level of the organization is created, which provides a mechanism for organizational learning. The overall process consists of the following cyclical processes and interactions (see also (Kim, 1993), Fig. 8):

(a) Individual level
  (1) Creating and maintaining individual mental models
  (2) Choosing for a specific context a suitable individual mental model as focus
  (3) Applying a chosen individual mental model for internal simulation
  (4) Improving individual mental models (individual mental model learning)
(b) From individual level to organization level
  (1) Deciding about creation of shared mental models
  (2) Creating shared mental models based on developed individual mental models
(c) Organization level
  (1) Creating and maintaining shared mental models
  (2) Associating to a specific context a suitable shared mental model as focus
  (3) Improving shared mental models (shared mental model refinement or revision)
(d) From organization level to individual level
  (1) Deciding about individuals to adopt shared mental models
  (2) Individuals adopting shared mental models by learning them
(e) From individual level to organization level
  (1) Deciding about improvement of shared mental models
  (2) Improving shared mental models based on further developed individual mental models

In terms of the three-level cognitive architecture described in (Van Ments and Treur 2021), applying a chosen individual mental model for internal mental simulation relates to the base level, learning, developing, improving, forgetting the individual mental model relates to the middle level, and control of adaptation of a mental model relates to the upper level. Moreover, interactions from individual to organization level and vice versa involve changing (individual or shared) mental models and therefore relate to the middle level, while the deciding actions as a form of control relate to the upper level.

This overview will provide useful input to the design of the computational network model for organizational learning and in particular the aggregation in it that will be introduced in Sect. 4.

3 The Self-modeling Network Modeling Approach Used

In this section, the network-oriented modeling approach used is briefly introduced. A temporal-causal network model is characterised by; here X and Y denote nodes of the network, also called states (Treur 2020b):

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

The following canonical difference (or related differential) equations are used for simulation purposes; they incorporate these network characteristics $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\boldsymbol{\eta}_Y$ in a standard numerical format:

$$Y(t+\Delta t) = Y(t) + \eta_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y} X_1(t), \ldots \boldsymbol{\omega}_{X_k,Y} X_k(t)) - Y(t)]\Delta t \tag{1}$$

for any state Y and where X_1 to X_k are the states from which Y gets its incoming connections. The available dedicated software environment described in (Treur 2020b, Ch. 9), includes a combination function library with currently around 50 useful basic combination functions. The above concepts enable to design network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. The examples of combination functions that are applied in the model introduced here can be found in Table 1.

Combination functions as shown in Table 1 and available in the combination function library are called *basic combination functions*. For any network model some number m of them can be selected; they are represented in a standard format as $\mathrm{bcf}_1(..)$, $\mathrm{bcf}_2(..)$, …, $\mathrm{bcf}_m(..)$. In principle, they use parameters $\pi_{1,i,Y}, \pi_{2,i,Y}$ such as the $\boldsymbol{\lambda}$, $\boldsymbol{\sigma}$, and $\boldsymbol{\tau}$ in Table 1. Including these parameters, the standard format used for basic combination functions is (with V_1, ..., V_k the single causal impacts):$\mathrm{bcf}_i(\pi_{1,i,Y}, \pi_{2,i,Y}, V_1, \ldots, V_k)$. For each state Y just one basic combination function can be selected, but also a number of them can be selected, what happens in the current paper; this will be interpreted as a weighted average of them according to the following format:

$$\begin{aligned}&\mathbf{c}_Y(\pi_{1,1,Y}, \pi_{2,1,Y}, \ldots, \pi_{1,m,Y}, \pi_{2,m,Y}, \ldots, V_1, \ldots V_k)\\ &\quad = \frac{\gamma_{1,Y}\mathrm{bcf}_1(\pi_{1,1,Y}, \pi_{2,1,Y}, V_1, \ldots V_k) + \ldots + \gamma_{m,Y}\mathrm{bcf}_m(\pi_{1,\mu,Y}, \pi_{2,\mu,Y}, V_1, \ldots V_k)}{\gamma_{1,Y} + \ldots + \gamma_{m,Y}}\end{aligned} \tag{2}$$

with *combination function weights* $\gamma_{i,Y}$. Selecting only one of them for state Y, for example, $\mathrm{bcf}_i(..)$, is done by putting weight $\gamma_{i,Y} = 1$ and the other weights 0. This is a convenient way to indicate combination functions for a specific network model. The function $\mathbf{c}_Y(..)$ can just be indicated by the weight factors $\gamma_{i,Y}$ and the parameters $\pi_{i,j,Y}$.

Table 1. The combination functions used in the introduced self-modeling network model

	Notation	Formula	Parameters
Advanced logistic sum	$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$	$[\frac{1}{1+e^{-\sigma(V_1+\ldots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}}](1 + e^{-\sigma\tau})$	Steepness $\sigma > 0$ Excitability threshold τ
Steponce	$\mathbf{steponce}_{\alpha,\beta}(..)$	1 if time t is between α and β, else 0	Start time α End time β
Hebbian learning	$\mathbf{hebb}_{\mu}(V_1, V_2, V_3)$	$V_1V_2(1 - V_3) + \mu V_3$	V_1,V_2 activation levels of the connected states; V_3 activation level of the self-model state for the connection weight Persistence factor μ
Maximum composed with Hebbian learning	$\mathbf{max\text{-}hebb}_{\mu}(V_1, \ldots, V_k)$	$\max(\mathbf{hebb}_{\mu}(V_1, V_2, V_3), V_4, \ldots, V_k)$	V_1,V_2 activation levels of the connected states; V_3 activation level of the self-model state for the connection weight Persistence factor μ
Scaled maximum	$\mathbf{smax}_{\lambda}(V_1, \ldots, V_k)$	$\max(V_1, \ldots, V_k)/\lambda$	Scaling factor λ
Euclidean	$\mathbf{eucl}_{n,\lambda}(V_1, \ldots, V_k)$	$\sqrt[n]{\frac{V_1^n+\ldots+V_k^n}{\lambda}}$	Order n Scaling factor λ
Scaled geometric mean	$\mathbf{sgeomean}_{\lambda}(V_1, \ldots, V_k)$	$\sqrt[k]{\frac{V_1*\ldots*V_k}{\lambda}}$	Scaling factor λ

Realistic network models are usually adaptive: often not only their states but also some of their network characteristics change over time. By using a *self-modeling network* (also called a *reified* network), a network-oriented conceptualization can also be applied to *adaptive* networks to obtain a declarative description using mathematically defined functions and relations for them as well; see (Treur 2020a; Treur 2020b). This works through the addition of new states to the network (called *self-model states*) which represent (adaptive) network characteristics. In the graphical 3D-format as shown in Sect. 4, such additional states are depicted at a next level (called *self-model level* or *reification level*), where the original network is at the *base level*.

As an example, the weight $\mathbf{\omega}_{X,Y}$ of a connection from state X to state Y can be represented (at a next self-model level) by a self-model state named $\mathbf{W}_{X,Y}$. Similarly, all other network characteristics from $\mathbf{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\mathbf{\eta}_Y$ can be made adaptive by including self-model states for them. For example, an adaptive speed factor $\mathbf{\eta}_Y$ can be represented by a self-model state named $\mathbf{H}_Y$, an adaptive combination function weight $\gamma_{i,Y}$ can be represented by a self-model state $\mathbf{C}_{i,Y}$.

As the outcome of such a process of network reification is also a temporal-causal network model itself, as has been shown in (Treur 2020b, Ch 10), this self-modeling network construction can easily be applied iteratively to obtain multiple orders of self-models at multiple (first-order, second-order, …) self-model levels. For example, a second-order self-model may include a second-order self-model state $\mathbf{H}_{\mathbf{W}_{X,Y}}$ representing the speed factor $\mathbf{\eta}_{\mathbf{W}_{X,Y}}$ for the dynamics of first-order self-model state $\mathbf{W}_{X,Y}$

which in turn represents the adaptation of connection weight $\boldsymbol{\omega}_{X,Y}$. Similarly, a persistence factor $\boldsymbol{\mu}_{\mathbf{W}_{X,Y}}$ of such a first-order self-model state $\mathbf{W}_{X,Y}$ used for adaptation, e.g., based on Hebbian learning (Hebb 1949) can be represented by a second-order self-model state $\mathbf{M}_{\mathbf{W}_{X,Y}}$. In particular, for the aggregation process for the formation of a shared mental which is a main focus of the current paper, in Sect. 4 s-order self-model states $\mathbf{C}_{i,\mathbf{W}_{X,Y}}$ will be used that represent the i^{th} combination function weight $\boldsymbol{\gamma}_{i,\mathbf{W}_{X,Y}}$ of the combination functions selected for a shared mental model connection weight $\mathbf{W}_{X,Y}$ (where the latter is a first-order self-model state).

4 The Adaptive Network Model for Organisational Learning

The case study addressed to illustrate the introduced model was adopted from the more extensive case study in an intubation process from (Van Ments et al. 2021a; Van Ments et al. 2021b). Here only the part of the mental models is used that addresses four mental states; see Table 2.

Table 2. The mental model used for the simple case study

States for mental models of persons A, B and organization O			Short notation	Explanation
a_A	a_B	a_O	Prep_eq_N	Preparation of the intubation equipment by the nurse
b_A	b_B	b_O	Prep_d_N	Nurse prepares drugs for the patient
c_A	c_B	c_O	Pre_oy_D	Doctor executes pre oxygenation
d_A	d_B	d_O	Prep_team_D	Doctor prepares the team for intubation

In the case study addressed here, initially the mental models of the nurse (person A) and doctor (person B) are different and based on weak connections; they don't use a stronger shared mental model as that does not exist yet. The organizational learning addressed to improve the situation covers:

1. Individual learning by A and B of their mental models through internal simulation which results in stronger but still incomplete and different mental models (by Hebbian learning). Person A's mental model has no connection from c_A to d_A and person B's mental model has no connection from a_B to b_B.
2. Formation of a shared organization mental model based on the two individual mental models. A process of unification takes place.
3. Learning individual mental models from the shared mental model; e.g., a form of instructional learning.

4. Strengthening these individual mental models by individual learning through internal simulation which results in stronger and now complete mental models (by Hebbian learning). Now person A's mental model has a connection from c_A to d_A and person B's mental model has a connection from a_B to b_B.

In this case study, person A and person B have knowledge on different tasks, and there is no shared mental model at first. Development of the organizational learning covers:

1. Individual learning processes of A and B for their separate mental models through internal simulation. By Hebbian learning (Hebb 1949), mental models become stronger but they are still incomplete. A has no knowledge for state d_A, and B has no knowledge for state a_B: they do not have connections to these states.
2. Shared mental model formation by aggregation of the different individual mental models.
3. Individuals' adoption of shared mental model, e.g., a form of instructional learning.
4. Strengthening of individual mental models by individual learning through internal simulation, strengthening knowledge for less known states of persons A and B (by Hebbian Learning). Then, persons have stronger and now (more) complete mental models.
5. Improvements on the shared mental model by aggregation of the effects of the strengthened individual mental individuals.

A crucial element for the shared mental model formation is the aggregation process. Not all individual mental models will be considered to have equal value. Person A may be more knowledgeable than person B, for example. And when they are equally knowledgeable, can they be considered independent sources, or have they just learnt it from the same source? In the former case aggregation of their knowledge lead to a stronger outcome than in the latter case. Based on such considerations, a number of context factors have been included that affect the type of aggregation that is applied: they are used to control the process of aggregation leading to a shared mental model in such a way that it becomes context-sensitive.

As in the network model, aggregation is specified by combination functions (see Sect. 3) of the first-order self-model states $\mathbf{W}_{X,Y}$ for the weights of the connections $X \rightarrow Y$ of the shared mental model, this means that these combination functions become adaptive (in a heuristic manner) in relation to the specified context factors. The influences of the context factors on the aggregation as indicated in Table 3 have been used to specify this context-sensitive control for the choice of combination function. For example, if A and B have similar knowledgeability, a form of average is supported (a Euclidean or geometric mean combination function), unless they are independent in which case some form of amplification is supported (a logistic combination function). If they differ in knowledgeability, the maximal knowledge is chosen (a maximum combination function). These are meant as examples of heuristics to illustrate the idea and can easily be replaced by other heuristics.

Table 3. Examples of heuristics for context-sensitive control of mental model aggregation applied in the example scenario

Context: knowledgeable	Context: dependency	Context: preference for type of quantity	Combination function type
A and B both not knowledgeable		Additive	Euclidean
		Multiplicative	Geometric mean
A and B both knowledgeable	A and B dependent	Additive	Euclidean
		Multiplicative	Geometric mean
	A and B independent		Logistic
A knowledgeable B not knowledgeable			Maximum
B knowledgeable A not knowledgeable			Maximum

The connectivity of the designed network model is depicted in Fig. 1. The base level of this model includes all the individual mental states, shared mental model states, and context states that are used to initiate different phases. Base level states can be considered as the core of the model.

The first-order self-model level includes context states that play a role in the aggregation such as context states for knowledgeability level, dependence level and preference for additive or multiplicative aggregation. Derived context states (e.g., representing that none of A and B is knowledgeable) are also placed here to make combinations of context states clearer by specifying in a precise way what it is that affects aggregation. This level lastly includes **W**-states representing the weights of the base level connections of the mental models to make them adaptive. At this first-order adaptation level there are a number of (intralevel) connections that connect **W**-states from individual mental models to shared mental models and conversely. The first type of such connections (from left to right) are used for the formation of the shared mental model: they provide the impact from the **W**-states of the individual mental models on the **W**-states of the shared mental model. This is input for the aggregation process by which the shared mental model is formed; in (Crossan et al. 1999) this is called feed forward learning. The second type of connections (from right to left) model the influence that a shared mental model has on the individual mental models. This models, for example, instruction of the shared mental model to employees in order to get their individual mental models better; in (Crossan et al. 1999) this is called feedback learning.

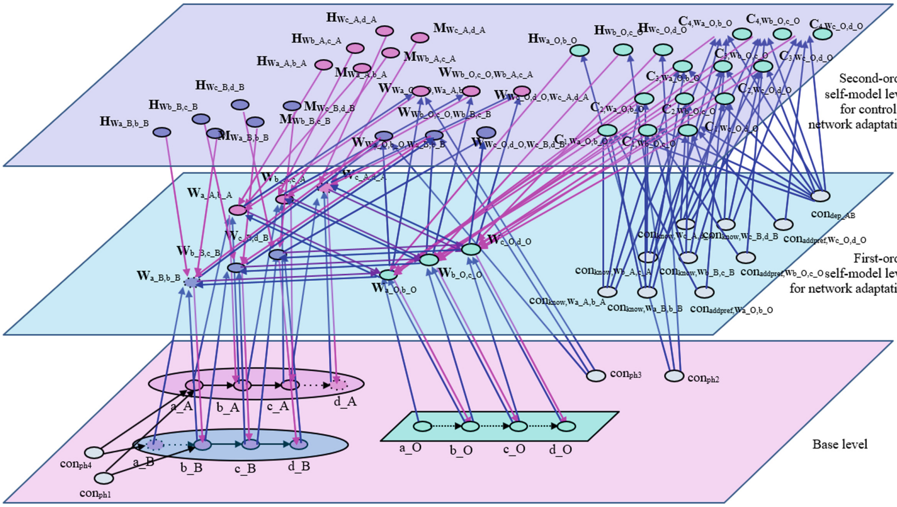

Fig. 1. The connectivity of the second-order adaptive network model

The second-order self-model level includes $\mathbf{W_W}$-, $\mathbf{M_W}$ and $\mathbf{H_W}$-states to control the adaptations of the network model run at the first-order self-model level. These $\mathbf{W_W}$-states (also called *higher-order* **W**-states) specifying the weights of the connections between **W**-states of the organization and individual mental models are placed here to initiate the learning from the shared mental model by the individuals (by making these weights within the first-order self-model level nonzero), once a shared mental model is available. Note that these $\mathbf{W_W}$-states are becoming nonzero if (in phase 3) a control decision is made to indeed let individuals learn from the formed shared mental model, but they also have a learning mechanism so that they are maintained after that as well: persons will keep relating (and updating) their individual mental model to the shared mental model. This type of learning for $\mathbf{W_W}$-states can be considered a form of *higher-order Hebbian learning*. The $\mathbf{H_W}$-states are used for controlling adaptation speeds of connection weights and $\mathbf{M_W}$-states for controlling persistence of adaptation.

To control the aggregation for the shared mental model connections there are second-order $\mathbf{C}_{i,\mathbf{W}}$-states in this level. Four different types of $\mathbf{C}_{i,\mathbf{W}}$-states are added to represent four different combination functions (see Table 1):

- $\mathbf{C_{1,W}}$ for the *logistic sum* combination function **alogistic**
- $\mathbf{C_{2,W}}$ for the *scaled maximum* combination function **smax**
- $\mathbf{C_{3,W}}$ for the *euclidean* combination function **eucl**
- $\mathbf{C_{4,W}}$ for the *scaled geometric mean* combination function **sgeometric**

So, there are four $\mathbf{C}_{i,\mathbf{W}}$-states for each shared mental model connection, which is three in total. Thus, the model has 12 $\mathbf{C}_{i,\mathbf{W}}$-states at the second-order self-model level to model the aggregation process. These second-order self-model states and the functions they represent are used depending on the context (due to the connections from the context states to the $\mathbf{C}_{i,\mathbf{W}}$-states), and the average is taken if more than one i has a nonzero $\mathbf{C}_{i,\mathbf{W}}$ for a given **W**-state.

More details of the model and a full specification can be found as Linked Data at URL https://www.researchgate.net/publication/354176039.

5 Example Simulation Scenario

Recall once more from Sect. 3 that aggregation characteristics within a network model are specified by combination functions. In particular, this applies to the aggregation of individual mental models in order to get shared mental models out of them. In this scenario, different combination functions are used to observe different types of aggregation while an organizational learning progresses by the unification of separate individual mental models. With a multi-phase approach, two individual mental models that are distinct in the beginning create the shared mental model of their organization by time, and there are effects of individuals and the organization on each other in different time intervals. Thus, it is possible to explore how aggregation occurs during an organizational learning progress.

To see the flow of these processes clearly, the scenario is structured in phases. In practice and also in the model, these processes also can overlap or take place entirely simultaneously. The five phases were designed as follows:

- **Phase 1**: **Individual mental model usage and learning**
- This relates to **(a)** in Sect. 2. Two different mental models for person A and B belonging to an organization are constructed and become stronger here in this phase. Hebbian learning takes place to improve their individual mental models by using them for internal simulations. Person A mainly has knowledge on the first part of the job, and person B has knowledge on the last part, thus A is the person who started the job and B is the one who finished it.
- **Phase 2: Shared mental model formation**
- This relates to **(b) and (c)** in Sect. 2. Unification and aggregation of individual mental models occur here. During this formation of shared mental model, different combination functions are used for different cases in terms of knowledgeability, dependence and preference of additivity or multiplicativity. Organizational learning takes place with the determination of the values of the **W**-states for the organization's general (non-personal) states for the job a_O to d_O. An incomplete and non-perfect shared mental model is formed and maintained by the organization.
- **Phase 3: Instructional learning of the shared mental model by the individuals**
- This relates to **(c) and (d)** in Sect. 2. Learning from the organization's shared mental model, which can be considered as learning from each other in an indirect manner, begins in this phase by the activation of the connections from the organization's general **W**-states to the individual **W**-states. Persons receive the knowledge from the shared mental model as a form of instructional learning. There is no need for many mutual one-to-one connections between persons since there is a single shared mental model.
- **Phase 4: Individual mental model usage and learning**
- This relates to **(d)** in Sect. 2. Further improvements on individual mental models of persons are observed by the help of Hebbian learning during usage of the mental

model for internal simulation in this phase. Person A starts to learn about task d (state d_A) by using the knowledge from the shared mental model (obtained from person B) and similarly B learns about task a (state a_B) that they did not know in the beginning. Therefore, these 'hollow' states become meaningful for the individuals. The individuals take advantage of the organizational learning.

- **Phase 5: Strengthening shared mental model with gained knowledge**
- This relates to **(e)** in Sect. 2. People of the organization start to affect the shared mental model as they gain improved individual knowledge by time. The activation of organization's general states causes improvements on shared mental model, and it becomes closer to the perfect complete shared mental model.

Figure 2 shows an overview of all states of the simulation. In Fig. 2, individual learning by using mental models for internal simulation (Hebbian learning) takes place in first phase happening between time 10 and 300. Only X_4 (d_A) and X_5 (a_B) remain at 0 because of the absence of knowledge. These 'hollow' states will increase in Phase 4 after learning during Phase 3 from the unified shared mental model developed in Phase 2. The **W**-states of the individuals representing their knowledge and learning slightly decrease starting from the end of Phase 1 at about 300 since the persistence factors' self-model **M**-states do not have the perfect value 1, meaning that persons forget. Since the persistence factor of B is smaller than of A, B's **W**-states decrease more in the second phase: it can be deduced that B is a more forgetful person.

Context states for different combination functions determine the aggregation pattern of the shared mental model in Phase 2. For 4 different functions, there are 12 $\mathbf{C}_{i,\mathbf{W}}$-states in total for the organization's three connections ($\mathbf{W}_{a\_O,b\_O}$, $\mathbf{W}_{b\_O,c\_O}$, and $\mathbf{W}_{c\_O,d\_O}$) with different activation levels. Some of them are even above 1 but this does not cause a problem because the weighted average of them will be taken (according to formula (2) in Sect. 3). The shared mental model is formed in this phase based on the context-sensitive control of the aggregation used.

The **W**-states of the organization's shared mental model have links back to the **W**-states of the individuals' mental models to make individual learning (by instructional learning) from the shared mental model possible. In Phase 3, all the higher-order self-model **W**-states (X_{47} to X_{52}, also called $\mathbf{W}_\mathbf{W}$-states) for these connections from the shared mental model's to the individuals' first-order **W**-states become activated. This models the instructional learning: the persons are informed about the shared mental model. Forgetting also takes place for the connections from the **W**-states of the organization's shared mental model to those of the individuals' mental models. It means that a fast-starting learning process becomes stagnant over time.

By observing Phase 4, it can be seen that after time 650, all the **W**-states of the individuals make an upward jump because of further individual learning.

In Phase 5, like in Phase 2, the **W**-states of the organization's shared mental model increase (due to the individual mental models that were improved in Phase 4) and get closer to a perfect complete shared mental model. This improved shared mental model in principle also has effect on individual mental models, as also the higher-order **W**-states are still activated here.

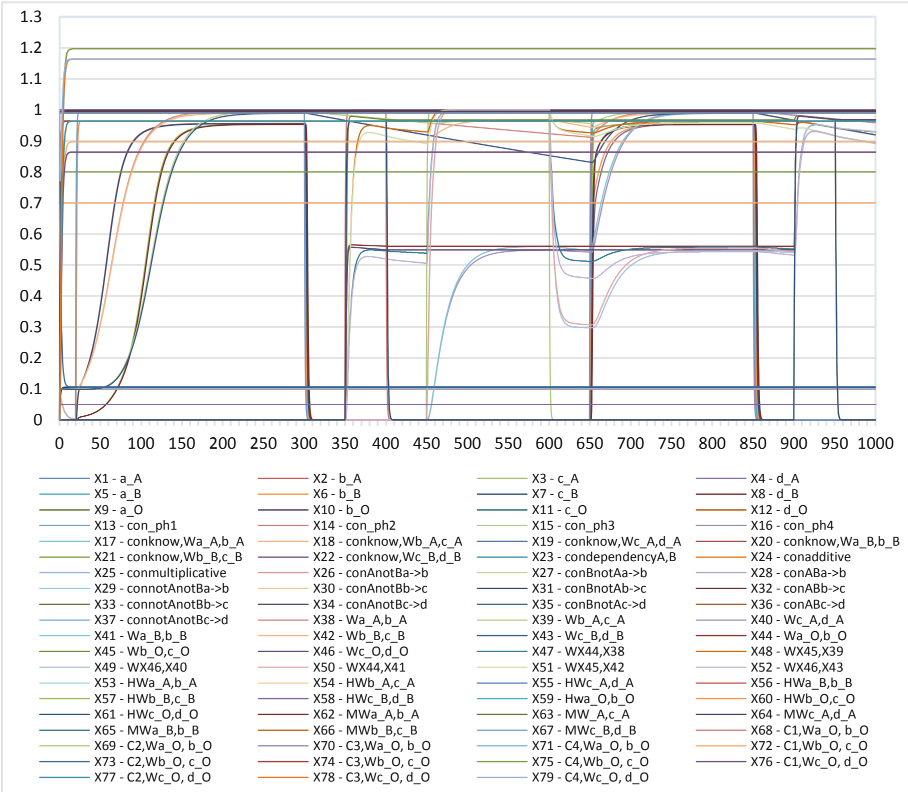

Fig. 2. Overview of the simulation scenario

6 Discussion

Organisational learning usually exploits developed individual mental models in order to form shared mental models for the organisation; e.g., (Kim 1993; Wiewiora et al. 2019). This happens by some form of aggregation. The current paper focuses on this aggregation process, which often depends on contextual factors. It was shown how a second-order adaptive self-modeling network model for organisation learning based on self-modeling network models described in (Treur 2020b) can model this process of aggregation of individual mental models in a context-dependent manner.

Compared to (Canbaloğlu et al. 2021) the type of aggregation used for the process of shared mental model formation was explicitly addressed and made context-sensitive. Different forms of aggregation have been incorporated, for example, Euclidean and geometric mean weighted averages, maximum functions and logistic forms. The choice of aggregation was made adaptive in a context-sensitive manner so that for each context a different form of aggregation can be chosen automatically as part of the overall process.

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