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Chapter 18
Discussion: Perspectives on Computational Modeling of Multilevel Organisational Learning

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Abstract In this chapter, key findings presented in this volume are summarised and evaluated to demonstrate the usefulness and great potential of the adaptive dynamical system approach based on self-modeling networks in providing a useful structure to formalise, analyse and simulate multilevel organisational learning processes. Moreover, future perspectives are discussed for further development and application based on what already has been achieved.

Keywords Multilevel organisational learning · Computational modeling · Adaptive dynamical systems · Self-modeling networks

18.1 Introduction

The literature on multilevel organisational learning is either conceptual or uses qualitative approaches (case studies or interviews) to explore learning processes and learning mechanisms, e.g., (Kim 1993; Crossan et al. 1999; Wiewiora et al. 2019, 2020). Although this literature has clarified the learning landscape, mathematical or computational formalisation of learning processes were missing. One of the challenges in examining organisational learning is its dynamic and context-sensitive nature. In addition, a range of factors influencing learning flows makes the process of learning complex, but at the same time rich and interesting to evaluate.

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Mathematical and computational modeling approaches provide a promising avenue for investigating learning processes in a more systematic manner. In this volume (Canbaloğlu et al. 2023), the self-modeling network modeling approach described in (Treur 2020a, b) was used as a vehicle. This approach is particularly useful as it allows to capture the interplay between different levels, adaptation mechanisms and control mechanisms involved, thereby addressing the high extent of context-sensitivity. The self-modeling network modeling enables us to address the effects of large numbers of contextual factors and has proven successful in modeling the three-level cognitive architecture for use, adaptation, and control of adaptation for mental models, see (Treur and Van Ments 2022). This modeling approach enabled to design and conduct simulation experiments and perform mathematical equilibrium analysis for different cases of multilevel organisational learning processes.

In this chapter, we consolidate the key findings and simulations presented in this book to demonstrate the usefulness and great potential of the self-modeling networks approach in providing a useful structure to formalise, analyse and simulate multilevel organisational learning processes as complex adaptive dynamical systems.

18.2 Self-Modeling Network Models

Following (Treur 2020a, b), a temporal-causal network model is characterised 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 $\boldsymbol{\omega}_{X,Y}$
- *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 above concepts enable us to design network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. By using a *self-modeling network* (also called a *reified* network), a network-oriented conceptualisation can also obtain a declarative description of adaptive networks using mathematically defined functions and relations, for more details, see (Treur 2020a, b), see also Chap. 3 of this volume (Canbaloğlu et al. 2023). In this case new states called *self-model states* are added to the network which represent adaptive network characteristics. In a graphical 3D-format 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 $\boldsymbol{\omega}_{X,Y}$ of a connection from state X to state Y is represented at a next level by a self-model state named $\mathbf{W}_{X,Y}$. Similarly, an adaptive speed factor $\boldsymbol{\eta}_Y$ can be represented by a self-model state named $\mathbf{H}_Y$ and an adaptive excitability threshold parameter $\boldsymbol{\tau}_Y$ can be represented by a self-model state named $\mathbf{T}_Y$. Moreover, a persistence factor $\boldsymbol{\mu}$ of a state Y of used for adaptation can be represented by a self-model state $\mathbf{M}_Y$. 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. In this way an adaptive learning speed for state $\mathbf{W}_{X,Y}$ can be modeled by introducing a second-order self-model state $\mathbf{H}_Z$ where $Z = \mathbf{W}_{X,Y}$ also simply denoted by $\mathbf{H}_{\mathbf{W}_{X,Y}}$. Similarly, second-order self-model states $\mathbf{M}_{\mathbf{W}_{X,Y}}$ can be used to model adaptive persistency of the learning. It has been proven in (Hendrikse et al. 2023) that any smooth adaptive dynamical system has a canonical self-modeling network representation, which shows that this format is very general; see also Chap. 16 of this volume (Canbaloğlu et al. 2023).

18.3 Computational Architecture for Use, Adaptation, and Control of Adaptation

To model learning processes within an organisation in a transparent manner, it is important to distinguish the different levels use, adaptation, control of adaptation of the processes: see Fig. 18.1, left-hand side for a conceptual cognitive architecture based on these levels. Following Kim (1993), in the first place learning can be conceptualised as adaptation of mental models. Secondly, although some examples of learning within an organisation may take place without exerting explicit control over it, many forms of learning require some explicit context-sensitive decisions to let them happen, for example, by a higher manager who has responsibility for the quality and learning of some group of members of the organisation. Therefore, not only 'adaptation' but also 'control of adaptation' from the abovementioned triple is crucial to obtain realistic context-sensitive computational models of learning within an organisation and multilevel organisational learning.

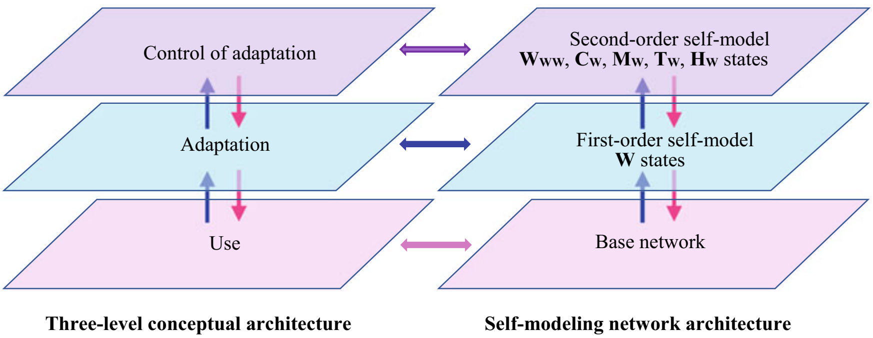

Fig. 18.1 Formalising the three-level conceptual architecture by a self-modeling network architecture

Self-modeling networks can easily be used to model each of these three levels and their interactions, as has been shown for different cases in different chapters in this volume (Canbaloğlu et al. 2023). In practically all chapters of this volume, for the level of adaptation, first-order self-model **W**-states $\mathbf{W}_{X_i,Y}$ have been used that represent weights of connections from mental model states X_i to a mental model state Y within individual or shared mental models that play a role within the organisation and its learning. This enables to differentiate the impacts from different mental model states X_i on a given mental model state Y. Alternative choices might have been possible as well, such as **T**-states $\mathbf{T}_Y$ for excitability thresholds for mental model states Y. However, then the impacts from different mental model states X_i on the given state Y cannot be differentiated, which is undesirable. Moreover, this would also have imposed limitations on the combination functions used for aggregation for the **W**-states, as they would need to include such a threshold parameter, while, for example, averaging functions usually do not have this.

18.4 What Has Been Addressed

In a self-modeling network format, control of any type of adaptation of network characteristics (modeled by first-order self-model states) can be modeled by second-order self-model states. In this volume (Canbaloğlu et al. 2023) for the control of adaptation, multiple second-order self-model states have been used for different types of control:

- $\mathbf{W}_{\mathbf{WW}}$-states for adaptive connectivity between the **W**-states
- $\mathbf{C}_{\mathbf{W}}$-states representing adaptive combination function weights for different types of adaptive aggregation of **W**-states
- $\mathbf{M}_{\mathbf{W}}$-states representing adaptive persistency of the learning for **W**-states
- $\mathbf{T}_{\mathbf{W}}$-states representing adaptive excitability thresholds for **W**-states
- $\mathbf{H}_{\mathbf{W}}$-states for adaptive learning speed for **W**-states

Table 18.1 provides a brief global overview of these self-model states with references to different chapters of this volume (Canbaloğlu et al. 2023) where they are used and for what purpose.

In Table 18.2, a more detailed overview is shown of different types of context-sensitive control for different types of learning. It can be seen here that $\mathbf{H}_{\mathbf{W}}$-states for adaptive adaptation speed of **W**-states have been used throughout for all types of learning to activate or accelerate the learning or stop it in a context-sensitive manner. Furthermore, $\mathbf{W}_{\mathbf{WW}}$-states for adaptive connection weights between **W**-states have been used for all types of learning to model context-sensitive effects, except individual learning. Moreover, $\mathbf{C}_{\mathbf{W}}$-states for adaptive aggregation for **W**-states have been used for context-sensitive shared mental model formation for feed forward learning.

Table 18.1 Overview of different types of control over the various adaptation processes for organisational learning addressed in this volume (Canbaloğlu et al. 2023); the indicated chapters refer to this volume

Control of adaptation via adaptive connectivity	Control of adaptation via adaptive aggregation	Control of adaptation via adaptive timing
Controlled adaptation of mental model **W**-states via $\mathbf{W_{WW}}$-states for adaptive connections between **W**-states: • between individual mental models in dyads, teams, or organisation: Ch 12–13 • between individual, team, and organisation mental models in feed forward and feedback learning: Ch 6–15	Controlled adaptation of mental model **W**-states via: • $\mathbf{C_W}$-states for adaptive weights of the combination functions used by **W**-states for aggregation: Ch 9–10 • $\mathbf{M_W}$-states for adaptive persistence of the learnt effects of **W**-states: Ch 6–10 • $\mathbf{T_W}$-states for adaptive excitability thresholds of **W**-states: Ch 15	Controlled adaptation of mental model **W**-states via • $\mathbf{H_W}$-states for adaptive adaptation speed of **W**-states: Ch 6–12, 14–15

18.5 Further Work Being Addressed

In further work it is being addressed how a virtual AI Coach can support safety in hospitals, in particular of medical teamwork. For an overview of this project, see (Canbaloğlu et al. 2022). This AI Coach has knowledge about the shared mental model that is used by a team and then can:

- Monitor in how far the shared mental model is followed
- Detect omissions or deviant actions
- Support the team to get back on track to the shared mental model

In addition, this AI Coach can play a central role in multilevel organisational learning by:

- Representing and maintaining shared mental models
- Supporting team members in learning or memorising a shared mental model
- Speaking up about errors
- Reporting errors to management

In the meantime, this has been explored computationally for some case studies concerning shared mental models in the neonatal domain:

- To support the breathing of the baby (Xu et al. 2023)
- To avoid postpartum depression (Weigl et al. 2023)
- To support speaking up behaviour (Doornkamp et al. 2023)

Another topic that needs further work concerns individual differences, for example, highly knowledgeable experts with deviant but good mental models. Also, the roles of leadership and organisational culture can be addressed further, for example, the effect of leadership on organisational learning, leadership change,

Table 18.2 More detailed overview of computational mechanisms for organisational learning and control explored in this volume (Canbaloğlu et al. 2023); the chapters indicated in the right-hand column refer to this volume

Types of learning addressed		Adaptation modeled by first-order self-model states	Control of adaptation modeled by second-order self-model states
Individual learning	Learning from internal simulation Observational learning by self-observation	Self-model W-states for Hebbian learning with upward and downward links to mental model base states Observation links or pathways from world states of self to mental model states; self-model W-states to control observation	Self-model H_W-states to control learning rate: Ch 6–10, 14–15. Self-model M_W-states to control persistence of learning of W-states: Ch 6–10, 14. Self-model T_W-states to control excitability thresholds of W-states: Ch 15
Dyad learning	Observational learning based on observation of others Instructional learning by communication	Self-model W-states for observation links from world states of others to mental model base states to control observation. Self-model W-states for Hebbian learning with upward and downward links to mental model states	Self-model H_W-states to control learning rate: Ch 12. Self-model W_{WW}-states for control of observation of other individuals: Ch 15. Self-model W_{WW}-states to control communication via self-model W-states for different individuals: Ch 12–13
Multilevel organizational learning	Feed forward learning	Aggregation of different individual W-states to form team and/or organization W-states. Using proper combination functions and proper parameters of them	Self-model H_W-states to control learning rate: Ch 6–12. Self-model W_{WW}-states to control feed forward learning: Ch 8, 11–15. Self-model C_W-states to control feed forward aggregation: Ch 9–10
	Feedback learning	Aggregation of individual W-states and team and/or organization W-states to update the individual W-states. Using proper combination functions and proper parameters of them	Self-model H_W-states to control learning rate: Ch 6–10. Self-model W_{WW}-states to control feedback communication: Ch 6–10, 13–15

the effect of culture on organisational learning, culture change, and organisational learning of culture.

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