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On Structure, Dynamics, and Adaptivity for Biological and Mental Processes: a Higher-Order Adaptive Dynamical System Modeling Perspective

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Abstract

To conceptualise biological and mental processes, often a dynamical systems perspective is suggested. In addition to dynamics, the structure of the contextual makeup or world configuration (of an organism or brain) plays a crucial role too, as well as adaptivity of the processes. This paper provides a conceptual perspective where the structure, dynamics, and adaptivity of these processes are distinguished and related to each other via adaptive dynamical systems. Moreover, it is shown how networks can be used to represent this conceptual perspective. Here an adaptive dynamical system of any order of adaptivity can be covered where any level can exert control over the level below. The approach is illustrated by case studies for higher-order adaptive evolutionary processes. One of these case studies shows a fifth-order adaptive dynamical system that models how due to bad environmental influences at a young age, epigenetic effects can lead to a lifelong mental disorder.

Keywords: structure and dynamics; dynamical system; higher-order adaptivity; self-modeling networks.

Introduction

Biological or mental processes are often considered to form complex dynamical systems, e.g., (Ashby, 1960; Port and Van Gelder, 1995). Within the literature, such dynamical systems and their processes are sometimes described by indicating what are called pathways, which roughly spoken can be considered as chains of causal mechanisms. On the one hand, pathways are based on the structure of the contextual world configuration, for example, parts of the physical or physiological makeup of an organism or of a brain and the causal relations or mechanisms it enables. On the other hand, due to this structure, pathways induce dynamics where states earlier in a pathway influence states further on in the pathway. From a philosophy of science perspective, it has been analysed that the importance of the role of the underlying structure makes that explanations only based on general laws do not work well for psychological and biological sciences. Instead, alternatives have been proposed giving structure a prominent role, for example, based on concepts such as physical or physiological 'makeup' (Treur, 2008; Treur, 2011) or 'mechanisms' (Bechtel, 2009; Bechtel, 2011; Bechtel and Abrahamsen, 2005).

Besides the two views on mental or biological processes or pathways from a structure perspective and from a dynamics perspective, also adaptivity often occurs. For example, for mental pathways, adaptive changes in pathway structures can occur due to other mental pathways that make learning happen. For biological pathways, adaptivity of pathway structures can also be based on other pathways for learning or improving skills, but as well by pathways for impacts from biological processes related to epigenetics and gene expression affecting the base pathway structures. The pathways for adaptation of other pathways have their own structure and dynamics and can also be adaptive themselves, which creates a form of recursion that enables higher-order adaptivity, realised by still other pathways.

In this paper, it will be shown how these concepts of structure, dynamics, and adaptivity of biological and mental processes can be distinguished and related, and how higher-order adaptive dynamical systems can successfully be used to obtain explanations and models based on them. The introduced perspective will be illustrated for a few examples of adaptive mental and biological processes.

In (Treur, 2020abc) it has been introduced and elaborated how self-modeling networks (also called reified networks) can be used to model multi-order adaptive biological, mental, and social processes in a convenient manner. Such networks use nodes for specific network states (called self-model states) to represent some of their own network characteristics, thus enabling them to change over time. In this paper, it will also be discussed how the structure of a pathway can be described by a network structure, the dynamics of the pathway by the network's dynamics, and adaptivity of the pathway by the network's adaptivity. Conceptualisation by networks (sometimes called circuits) can also be found in biological literature such as (Alon, 2019; Alon, 2023; Westerhoff et al, 2014a; Westerhoff et al, 2014b). Following (Hendrikse, Treur, Koole, 2024; Treur, 2021), it will be pointed out here that any smooth (higher-order) adaptive dynamical system can be described by its canonical (higher-order) self-modeling network representation. Therefore, using networks to describe higher-order adaptive dynamical systems is universal: it does not introduce any fundamental limitation.

Structure, Dynamics, and Adaptivity

As discussed above, the structure of a process or pathway can be considered as the contextual world configuration that enables its dynamics, for example, parts of the physiological structure of an organism or of a brain. As a metaphor, the structure of a pathway can be visualised as a river bed in a landscape and its dynamics as the river's water flow induced by this river bed. The river metaphor is used to distinguish beween structure and dynamics and their relation; see the lower part in the upper half of Fig. 1. Note that dynamics usually is conditional with respect to some situational

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conditions other than the pathway structure. In the river metaphor, some of such situational conditions concern that rain has fallen and that the water is not frozen. Another example of structure and dynamics of pathways for mental or neural proceses is propagation of activation of mental states or of neurons or areas in the brain; see the lower part in the lower half of Fig. 1.

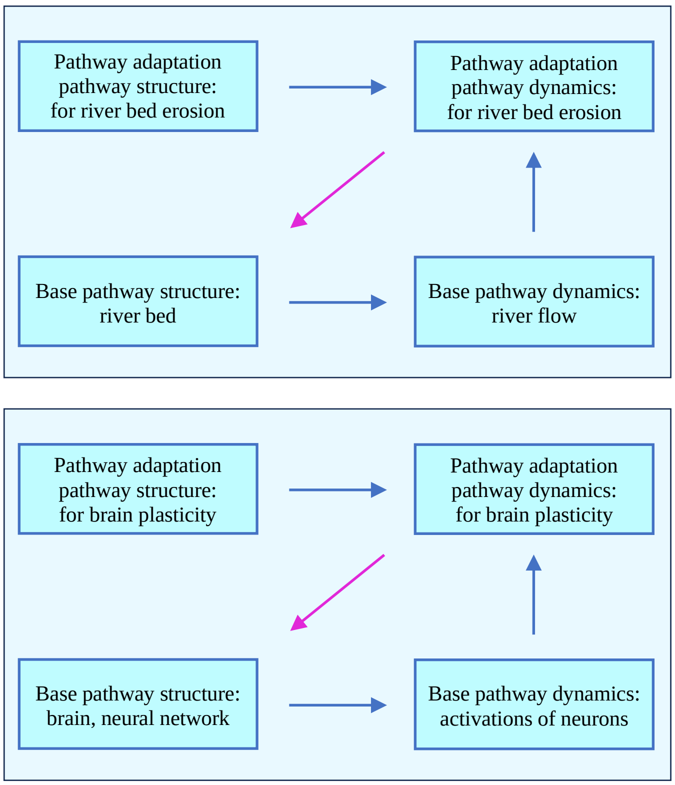

Figure 1: Two illustrations of pathway adaptation pathways: one for the river metaphor with erosion (upper part) and one for neural processing and brain plasticity (lower part)

In realistic examples, pathway structures often show adaptivity over time. For the river metaphor, this can for example take place by another pathway: by erosion of the landscape, the river bed is reshaped or reconfigured over time. This change in pathway structure in turn will also change the pathway dynamics of the flow of the river. Conceptually, this erosion pathway works as a pathway for adaptation of another pathway (a pathway adaptation pathway, for short); its dynamics brings about a change in the other pathway's structure (the river bed) which in turn will also change that pathway's dynamics (the river flow). For mental pathways, such adaptive changes in pathway structure can for example occur due to mental pathway adaptation pathways that make learning happen, for example, by strengthening connections (via synapses) based on Hebbian learning (Hebb, 1949). For biological pathways, adaptivity of pathway structures can also be based on biological pathway adaptation pathways for learning or improving certain skills by exercising, and as well by pathways for impacts from other biological processes such as transcription of genes affecting (via their related mRNA and enzymes) the considered pathway structures. Via epigenetic influences such processes can be dependent on the environmental context (Nigg, 2023).

As any pathway, a pathway adaptation pathway has its own structure and dynamics, as shown in Fig. 1 for the river metaphor (upper half) and for neural processes (lower half). Also in this case, its dynamics is affected by its structure (indicated by the blue horizontal arrow in the upper part of each of the two halfs in Fig. 1) but can also have influences from the base pathway dynamics as indicated by the blue upward arrows in Fig. 1. This upward blue arrow indicates, for example, that the strength of the flow of a river often will affect the erosion process of the river bed too.

An illustration for the case of neural processing and brain plasticity can be found in the lower half of Fig. 1. In this case, the upper part describes the structure and dynamics of the pathway for plasticity of the network of neurons, for example, the pathway based on the mechanisms of Hebbian learning that can strengthen connections. Here, the blue upward arrow indicates that this adaptation process depends also on the activation levels of the connected neurons.

Pathways for adaptation of other pathways can also be adaptive themselves; this creates second-order adaptivity of pathways. Such second-order adaptivity is realised by still other pathways. Moreover, this conceptualisation can be repeated for an arbitrary number of adaptation orders or levels; this creates a form of recursion that makes higher-order adaptivity. The case of second-order adaptive pathways is illustrated in Fig. 2 again for the two examples addressed in Fig. 1: for the river metaphor and for neural processing.

For the river metaphor, second-order pathway adaptivity occurs when measures are taken to control (modulate or block) erosion; see the upper half of Fig. 2 for the river metaphor. For example, this often takes place when a river goes through a city where a river bed that continuously changes its position is highly undesirable. By adding solid material to the river bed, erosion can then be minimised or even (almost) completely blocked. Usually such measures are taken with higher priority when more erosion is observed, which is indicated by the upward blue arrow from first-order pathway adaptation pathway dynamics to second-order pathway adaptation pathway dynamics.

For a conceptualisation of second-order adaptivity for neural processes in particular, see the lower half of Fig. 2, which illustrates the concepts for neuroscience. This second-order adaptation level can be used to make the first-order adaptation context-sensitive as for neuroscience is addressed by the metaplasticity literature such as (Abraham and Bear, 1996; Robinson et al, 2016; Sjöström et al, 2008). For example, the 'Plasticity Versus Stability Conundrum' in neuroscience (Sjöström et al, 2008) can be conceptualised and modelled in this way by applying context-sensitive control to the pathway adaptation pathway for plasticity of the brain. At that adaptivity control level, it can be specified under which contextual circumstances plasticity should have priority and under which stability. Also the more specific metaplasticity principle 'Adaptation accelerates with increasing stimulus exposure' from neuroscience as formulated by (Robinson et al, 2016) can be conceptualised and modelled in this way: for example by introducing adaptive first-order adaptation speed at that adaptivity control level and specifying under which circumstances that adaptation speed should be high and under which low.

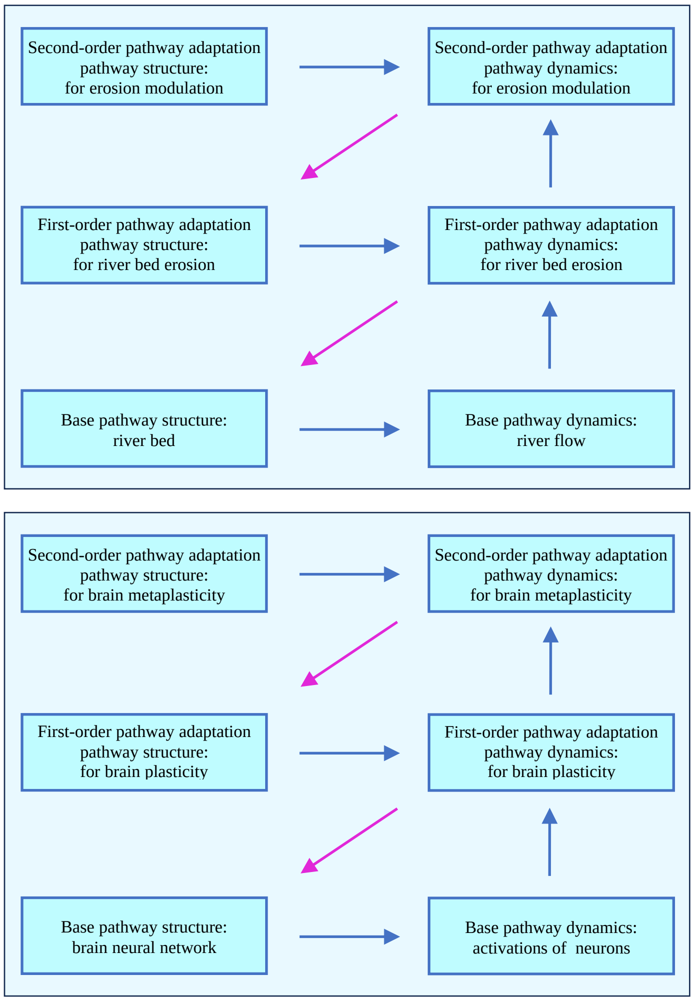

Figure 2: Two illustrations of second-order pathway adaptation pathways: one for the river metaphor with erosion and control of erosion (upper part) and one for neural processing, brain plasticity, and metaplasticity to control plasticity (lower part).

Modeling Adaptive Dynamical Systems by Self-Modeling Networks

Up till now, it was pointed out how conceptually from a higher-order adaptive dynamical systems perspective the structure, dynamics and adaptivity of biological and mental pathways or processes can be analysed and modeled. However, no detailed formalisation or modeling format for such a dynamical system was discussed. In this section, it will be explained how such higher-order adaptive dynamical systems can be described by higher-order adaptive (self-modeling) network representations. Here, the structure of a pathway corresponds to a subnetwork or path within a network structure, the induced dynamics of the pathway corresponds to the network's dynamics, and adaptivity of the pathway to the network's adaptivity.

Following (Treur, 2020abc), a temporal-causal network model uses nodes X and Y, also called states, with real number activation values $X(t)$ and $Y(t)$ over time t and network structure defined by the following network characteristics. Connectivity characteristics: connections from a state X to a state Y and their weights $\boldsymbol{\omega}_{X,Y}$. Aggregation characteristics: for any state Y, a 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 aggregated causal impact.

Based on the network structure defined above, the following canonical difference (or equivalent differential equations) define the network's dynamics, incorporating these network characteristics $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$ and $\boldsymbol{\eta}_Y$ in this standard numerical format (1):

$$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \dots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)]\,\Delta t$$

for any state Y and where X_1 to X_k are the states from which Y gets its incoming connections. The software environment described in (Treur, 2020a, Ch. 9), includes a combination function library with for example this logistic function (2):

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

Here the variables V_i are used for the single impacts $\boldsymbol{\omega}_{X_i,Y}X_i(t)$, $\boldsymbol{\sigma}$ is a steepness parameter and $\boldsymbol{\tau}$ an excitability threshold parameter. This software environment and its documentation can be downloaded via

https://www.researchgate.net/publication/368775720
https://www.researchgate.net/publication/369596699
https://www.researchgate.net/publication/368776149

To model adaptive dynamical systems, adaptive network models can be used: then not only a network's state activation levels but also some of the network structure characteristics can change over time. By using a *self-modelling network* (also called a *reified* network), a network-oriented conceptualization can also be applied to adaptive networks; see (Treur, 2020abc). This can be done through the addition of new states to the network (called *self-model* or *reification* states) which represent (adaptive) network characteristics. By changing the activation values of such self-model states over time, the corresponding network characteristics become adaptive. 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 can be represented (at a next self-model level) by a self-model state named $\mathbf{W}_{X,Y}$. In this way, for example, Hebbian learning (Hebb, 1949) can be modelled, sometimes formulated simply by 'Neurons that fire together, wire together' (Shatz, 1992). In such a case, in equations (1), for the connectivity characteristics $\boldsymbol{\omega}_{X_i,Y}$ the values $\mathbf{W}_{X_i,Y}(t)$ are used (3):

$$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y([\mathbf{c}_Y(\mathbf{W}_{X_1,Y}(t)X_1(t), \dots, \mathbf{W}_{X_k,Y}(t)X_k(t)) - Y(t)]\,\Delta t$$
$$dY(t)/dt = \boldsymbol{\eta}_Y[\mathbf{c}_Y(\mathbf{W}_{X_1,Y}(t)X_1(t), \dots, \mathbf{W}_{X_k,Y}(t)X_k(t)) - Y(t)]$$

In such a way, any of the network characteristics $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\boldsymbol{\eta}_Y$ can be made adaptive by including self-model states for it. These self-model states are handled in the same way as other states, so they have their own network characteristics and for their dynamics canonical equations (1) are applied to them as well. In Table 1, an overview is shown of the concepts used to define network structure, network dynamics and network adaptivity and their formalisation as discussed in this section.

Table 1: Network structure, dynamics and adaptivity: concepts and their formalisation.

	Concepts	**Formalisation**
Network structure	States Network characteristics ▪ connectivity ▪ aggregation ▪ timing	X and Y and connections between them $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\boldsymbol{\eta}_Y$ ▪ real numbers for connection weights: $\boldsymbol{\omega}_{X,Y}$ ▪ mathematical functions: $\mathbf{c}_Y$ ▪ real numbers for speed factors: $\boldsymbol{\eta}_Y$
Network dynamics	Canonical difference or differential equation for state values over time	$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \dots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)]\,\Delta t$ $\frac{dY(t)}{dt} = \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \dots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)]$
Network adaptivity	Canonical difference or differential equation using adaptive network characteristics	$Y(t+\Delta t) = Y(t) + \mathbf{H}_Y(t)[\mathbf{c}_Y(\mathbf{W}_{X_1,Y}(t)X_1(t), \dots, \mathbf{W}_{X_k,Y}(t)X_k(t)) - Y(t)]\,\Delta t$ $\frac{dY(t)}{dt} = \mathbf{H}_Y(t)[\mathbf{c}_Y(\mathbf{W}_{X_1,Y}(t)X_1(t), \dots, \mathbf{W}_{X_k,Y}(t)X_k(t)) - Y(t)]$

As the outcome of a process of network self-modeling results also in a temporal-causal network model itself (Treur, 2020b, Ch 10), this self-modelling 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 $\mathbf{W}_{c,\mathbf{W}_{X,Y}}$ representing the adaptive connection weight $\boldsymbol{\omega}_{c,\mathbf{W}_{X,Y}}$ of a connection from context state c to $\mathbf{W}_{X,Y}$ which in turn represents the adaptive connection weight $\boldsymbol{\omega}_{X,Y}$. This second-order adaptation level can be used to control the (first-order) adaptation in a context-sensitive manner as addressed by the metaplasticity literature such as (Abraham and Bear, 1996; Robinson et al, 2016; Sjöström et al, 2008).

Any smooth dynamical system has a canonical representation as a network and any smooth (multi-order) adaptive dynamical system has a canonical representation as a (multi-order) self-modeling network, as is shown in (Treur, 2021a; Hendrikse et al, 2023). Therefore, compared to adaptive dynamical systems in general, the network-oriented modeling approach used does not introduce any fundamental limitations concerning what it can model. This has also been confirmed by applications in practice, e.g., (Treur and Van Ments, 2022; Canbaloğlu et al, 2023; Hendrikse, et al, 2024).

In next section, it is discussed how the network-oriented perspective on conceptualisation and formalisation of adaptive dynamical systems can be used to formalise and model the structure, dynamics and adaptivity of pathways and their relations as discussed earlier.

Using Self-Modeling Networks to Model Structure, Dynamics and Adaptivity

For the second-order adaptivity case, the overall view of the mapping (indicated by the dashed lines) is displayed in Fig. 3. At the base level, the structure of a pathway is described by a network structure and the dynamics of the pathway by this network's dynamics. At the first-order pathway adaptation level, the pathway adaptation structure is described by a first-order self-model network structure and the pathway adaptation dynamics by the dynamics of this first-order self-model network. Similarly, at the second-order pathway adaptation level, the second-order pathway adaptation pathway structure is mapped on the second-order self-model network structure and the second-order pathway adaptation pathway dynamics by that second-order self-model network's dynamics. This can be generalised to an arbitrary number of adaptation levels.

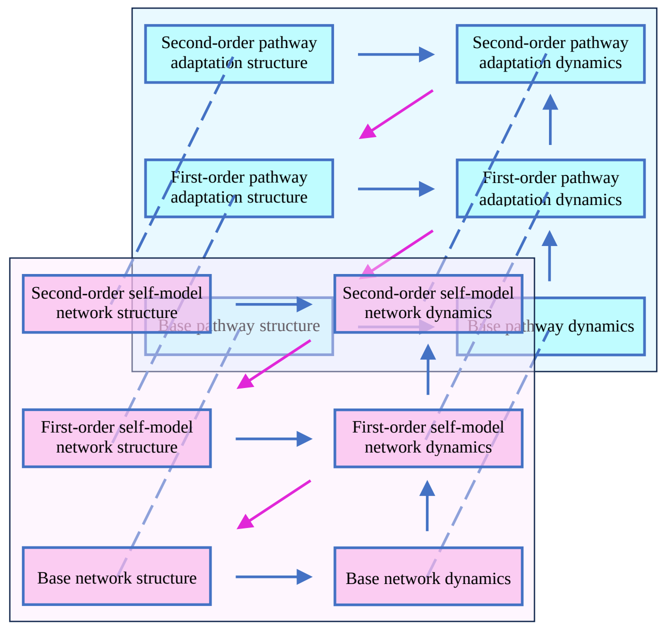

Figure 3: How structure, dynamics and adaptivity can be mapped onto self-modeling network concepts.

Describing Evolutionary Processes by Adaptive Pathways for Multiple Control Levels

Next, the mapping introduced in the previous section is illustrated for evolutionary processes as described within biology. Evolutionary adaptation often concerns affecting existing pathways by adding new pathways that change the structure of these existing pathways as a form of control, for example for upregulating or downregulating them. In this way, levels of control are created where the structure of a pathway at one level is changed (i.e., adapted) by the dynamics of a pathway at the next level, like in Fig. 2, but then with an arbitrary number of levels. Using a network representation, control of a pathway can be modeled, for example, by strengthening or weakening one or more connections within such a pathway's structure. In a self-modeling network representation, self-model states at the next level can be used for this. In Fig. 4 an abstract example is shown of such a self-modeling network model for fourth-order adaptivity of the type that can be found in evolutionary processes. Here, for the sake of simplicity, at each level the pathway structure is described by a context state representing that the necessary environment (makeup) is functional and a self-model state for the lower-level pathway connection plus a horizontal connection from the context state to this self-model state. By this level's dynamics, activation of this self-model state in turn controls the connection one level lower.

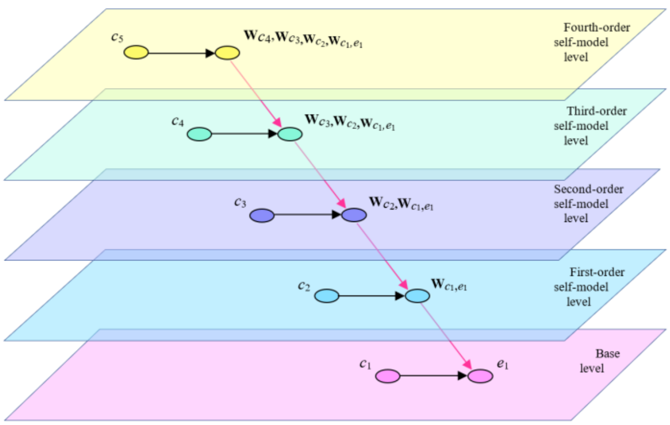

Figure 4: Self-modeling network structure for 4th-order adaptation in evolutionary processes via levels of control

A similar self-modeling network model has been applied in (Treur, 2019) to model a case study of evolutionary processes from (Fessler et al., 2015), e.g., see

> 'Also of relevance here, one form of disgust, pathogen disgust, functions in part as a third-order adaptation, as disease-avoidance responses are up-regulated in a manner that compensates for the increases in vulnerability to pathogens that accompany pregnancy and preparation for implantation – changes that are themselves a second-order adaptation addressing the conflict between maternal immune defenses and the parasitic behavior of the half-foreign conceptus (Fessler, Eng & Navarrete, 2005; Jones et al., 2005; Fleischman & Fessler, 2011).' (Fessler et al., 2015)

This quote considers three levels of adaptation for the first trimester of pregnancy. But also considering the occurrence of pathogens a form of adaptation for the wider ecological context, pathways for the following four adaptation orders can be distinguished; via its dynamics, each of these adaptations controls the pathway of the previous adaptation:

- **First-order adaptation** Pathogens occur, with pathways negatively modulate the existing pathways for good health.
- **Second-order adaptation** An internal defense system occurs, with pathway negatively modulating the pathogens pathway.
- **Third-order adaptation** For pregnancy, a pathway is added to downregulate the defense system's pathway during the first trimester, thus protecting the half-foreign conceptus.
- **Fourth-order adaptation** Disgust during first-trimester pregnancy adds a pathway to make the downregulation of the immune system less strong via the behavioural immune system: by disgust potential pathogens in the external world are avoided so that less risks are taken.

This evolutionary perspective where the pathways of existing adaptations are conserved and only controlled or regulated by other pathways is in line with the idea of 'frozen accidents' or 'frozen metabolic accidents':

> 'There is historical evidence that it is hard to transition to a fundamentally different reaction network; life has not ever done it as far back as we have evidence. Evolutionary biologists might describe this phenomenon as a "frozen metabolic accident" (Leister, 2019; Shi, Bibby, Jiang, Irwin, Falkowski, 2005). (…) In short, once a (bio)chemical system begins to harbor multiple connected subsystems, it becomes essentially unalterable because a significant change would reverberate through all interconnected subsystems. This would be true for purely chemical complex reaction networks as well as for biological ones.' (Preiner et al, 2020), p. 7710.

For more literature about this concept and its relation to the 'metabolism-first' hypothesis on the origin of life, see (Doig, 2017; Ikehara, 2022; Koonin, 2017; Maury, 2018; Muchowska, et al, 2020).

Modeling Adaptive Pathways Involving Genetics and Epigenetics

A similar architecture based on a tower of control levels can be used to model how in a cell the expressed genes control what types of mRNA are produced, which is turn control which active enzymes are produced to change the physiological makeup of the organism which in turn affects the metabolism, see Fig. 5. In this section it is briefly discussed how aspects of genetics and also of epigenetics can be addressed from the perspective described here.

First, to explore the role of genetics, consider the example of a biological network for *E. coli*, described in (Jonker et al, 2008, Fig. 1 left hand side). This example describes on the one hand how bacteria generate and control their behaviour based on their genetical background, taking into account expressed genes, mRNA, and active enzymes and the related transcription and translation processes. For the general perspective on modelling the cell's metabolic and life processes as biochemical networks, see also (Alon, 2019; Alon, 2023; Westerhoff et al, 2014a; 2014b). From the perspective of higher-order adaptation of pathways as considered here, the *E. coli* example can be modeled in a simplified, abstract way as shown in Fig. 5; here the term flux is used to indicate the base metabolism.

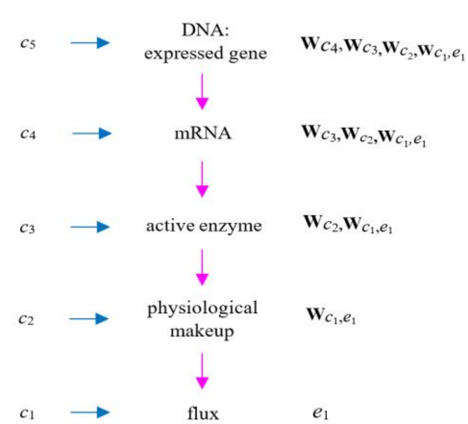

Figure 5: Multiple levels of control for pathways in a cell

Horizontal arrows indicate the pathways within the different levels from the contextual world state c_i for that level, for example for mRNA production (i=4) or enzyme production (i=3). Vertical arrows indicate control of the level below.

In recent years, studying the role of epigenetics in mental and physical disorders has received more and more attention in the literature, e.g., (Cecil, Neumann, Walton, 2023; Cecil and Nigg, 2022; Nigg, 2023). As an extension of the model described in Fig. 5 incorporating genetics, a model covering epigenetics as well has been designed, following the perspective of (Nigg, 2023). An adaptive dynamical system model such as the one depicted in Fig. 6 explains and simulates the development of a mental disorder such as anxiety disorder, PTSD, and ASD, see also (David, Kalibala, Pichon, Treur, 2024; Gunjača, Samhan, Treur, 2024; Kathusing, Samhan, Treur, 2024).

Here, for the pathway for the epigenetic effects to control expression of genes, one more adaptation level is added above the genetic level for expressed genes. This control of the expression of the relevant genes is influenced by environmental circumstances, which is modeled by the long blue upward arrows from base level to fifth-order self-model level.

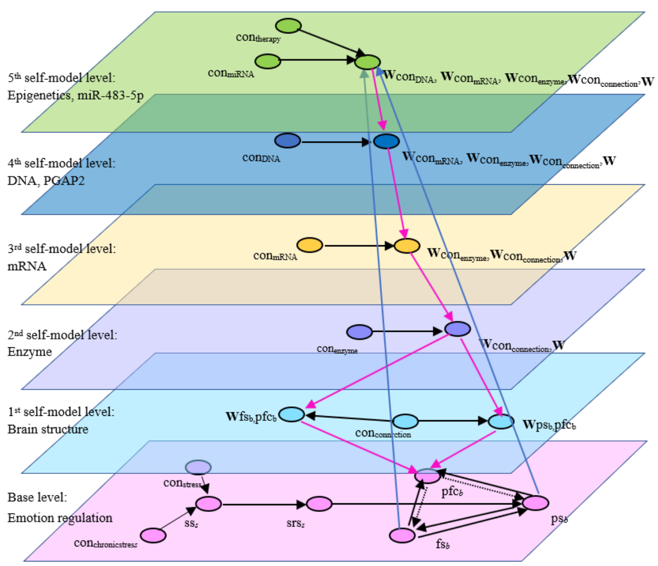

Figure 6: Multiple control levels up to fifth-order to model both genetic and epigenetic effects for the development of a mental disorder, illustrated for anxiety disorder. Adopted from (Kathusing et al, 2024).

Discussion

In this section it is discussed how the perspective based on structure, dynamics and adaptivity put forward here connects to some related topics in the literature. First, it already has been discussed above that the ‘frozen metabolic accident’ and the ‘metabolism-first’ hypothesis on the origin of life relate to the perspective discussed here (Preiner et al, 2020; Ralser, 2018; Yarus, 2011; Doig, 2017; Ikehara, 2022; Koonin, 2003, 2017; Maury, 2018; Muchowska, Varma, Moran, 2020). The idea is that a complex chemical reaction network for base metabolism emerged first. Probably, naturally occurring catalysts were modulating this. On top of this chemical network, other structures later emerged. The ‘frozen metabolic accident’ hypothesis can explain how such pathways developed later on, do not change the existing pathways but add adaptation pathways on top of them to control them. The perspective addressing multiple levels of control as contributed by the current paper may provide a useful way to describe and analyse such structures developed via subsequent steps during evolution.

Next, the general principle of temporal factorisation introduced in (Treur, 2007ab) postulates an important role for mediating states in dynamics. Such a mediating state indicates a structure in the present world or brain state which (1) emerges based on the earlier dynamics, and (2) in turn affects the later dynamics. This is in line with pictures like in Figs. 1 and 2, where the indicated structures on different levels indeed play a mediating role between earlier dynamics and later dynamics. In (Treur, 2021b, 2022) it has been shown how the more specific notion of criterial causation introduced in (Tse, 2013) to describe neural dynamics and plasticity is a special case of temporal factorisation, in this case applied to the brain: the criteria for criterial causation also form a specific structure (in the brain) that mediates between past and future dynamics.

In recent work from the philosophical perspective based on mechanisms mentioned in the introduction, also the importance of different levels of control has been emphasized (Bechtel, 2022; Bich and Bechtel, 2022a; Bich and Bechtel, 2022b). This provides support from the philosophical side for the perspective using multiple control levels discussed here. Not only hierarchical control levels but also heterarchical ones are considered in this literature. Also in the approach discussed here, control levels can be but do not need to be hierarchical. As an example, strange loops (Hofstadter, 1979, 2006, 2007) are cyclic control level structures which have been shown to work well in (Treur, 2020b), Ch 8, pp. 186-208, and (Anten, Earle, Treur, 2020). Within the area of Systems Biology such towers of control levels have been discussed too, for example, see (Hofmeyr and Westerhoff, 2001; Bevilacqua, Wilkinson, Dimelow et al, 2008).

Another related topic is the function–behavior–structure framework from design science (Bott and Mesmer, 2019, 2023; Gero and Kannengiesser, 2004, 2014; Sanderson, Chaplin, Ratchev, 2019). In that case also a notion of function is added to the behavior-structure distinction that corresponds to our dynamics-structure distinction.

Finally, the topic addressed here also relates to approaches to reasoning where reasoning steps make use of a world structure model. For example, in (Weyhrauch, 1980), socalled simulation structures and semantic attachments with them are used for this purpose. Other approaches of using world structure models in reasoning and its dynamics can be found in (Johnson-Laird, 1983; Leemans et al, 2002; Meyer and Treur, 2002; Treur, 1988, 1991; Treur and Willems, 1994; Treur and Van Ments, 2022; Van Ments and Treur, 2021).

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