Managing Multi-Site Artificial Neural Networks' Activation Rates and Activation Cycles
- Demonstrating the Effects of Activation Types on ANN-based Cyber-Physical Production Systems

Marcus Grum(https://orcid.org/0000-0002-3815-4238)

J.-Chair of Business Information Systems, esp. AI-based Appl. Sys.,
University of Potsdam, Potsdam 14482, Germany,
marcus.grum@uni-potsdam.de,

Abstract. With the further development of more and more production machines into cyber-physical systems, and their greater integration with artificial intelligence (AI) techniques, the coordination of intelligent systems is a highly relevant target factor for the operation and improvement of networked processes, such as they can be found in cross-organizational production contexts spanning multiple distributed locations. This work aims to extend prior research on managing their artificial knowledge transfers as coordination instrument by examining effects of different activation types (respective activation rates and cycles) on by Artificial Neural Network (ANN)-instructed production machines. For this, it provides a new integration type of ANN-based cyber-physical production system as a tool to research artificial knowledge transfers: In a design-science-oriented way, a prototype of a simulation system is constructed as Open Source information system and a rhythmic state descriptions approach for dynamic systems is designed. These are demonstrated thereafter. Findings show that this simulator (I) enables research on ANN activation types in production networks, (II) illustrates ANN-based production networks disrupted by activation types and clarifies the need for harmonizing them, and (III) derives conceptual management interventions. This study establishes the importance of site-specific coordination mechanisms and novel forms of management interventions as drivers of efficient artificial knowledge transfer.

Keywords: Artificial Neural Networks, Cyber-Physical Systems, Symbiotic Knowledge Management, Artificial Knowledge Transfer, Experiments, Simulation.

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1 Introduction

Traditionally, production machines are considered as more or less static tools being programmed with software and hardware routines, which are used to realize value-adding production steps in order to finalize workpiece carriers [1]. Aside analogous and digital signals that are generated because of physical sensory information, production machines can be accompanied with Digital Twins in Industry 4.0 [2] and Internet of Things [3] contexts to capture beneficial aspects, such as flexibility [4], reliability [5], individualization [6]. Due to their conceptualization as cyber-physical systems [7], these kinds of tools enable embedded or remote signal processing, autonomous communication as well as more sophisticated intelligent task realization [8]. Although isolated prototype concepts start bringing several facets of Artificial Intelligence (AI) to such machines [9, 10], common AI usage has not yet been standardized in application systems. Hence, AI-based knowledge flows at production machines are rather inefficient [11].

These missing standards are particularly problematic if AI is introduced to networks of production machines, such as in organization-wide networks of CPS or cross-organization-wide interacting CPS networks [12]. The controlling of multi-site production facilities via Artificial Neural Networks (ANN) - each machine and site can be represented as individual *cognitive production network* [13] - is challenging because of different characteristics: Activation patterns might vary at machine-, site- and vendor-specific levels for instance as well as follow organization-specific routines and processes. So, AI-based knowledge flows in overarching, interwoven cognitive production networks might become destructive [14] and inefficient [15] in the entire network's context. Reasons can be found at different activation rates and activation cycles, so that, in a worse case, correctly working outcomes of ANN activated are overwritten or lost in disharmonious ANN-sub-structures. If it was possible to bring isolated, machine-specific or site-specific ANN networks in harmony, one can expect joint multi-site ANN-based systems to have (a) more efficient knowledge transfers as individual machines and facilities can adapt to the specific knowledge conversion, (b) destructive activations of sub-systems can be reduced, so that for instance waste, energy and time consumption can be reduced in cross-organization production chains, and (c) ANN-based networks become controllable in a way that management interventions can be applied to improve artificial knowledge transfers in advance.

This article works out the prototype of a concept about multi-site ANN-based application systems as a research instrument in form of a simulation system. It clarifies inefficient and destructive ANN-based knowledge flows and corresponding improvement of knowledge transfers by management intervention in selected production scenarios. Thus, the following research will address the improvement of ANN knowledge transfers and focuses on the following research question:

> *"How can different activation types of rate and cycle combinations in multi-site ANN be researched and improved?"*

The research does not intend to provide a sophisticated empirical proof of improved ANN knowledge transfers because of managed multi-site ANNs. It rather intends to clarify the basis of such an instrument in production contexts that will be verified in on-building empirical research, experiments and simulation runs. This research further contributes with a more versatile kind of state descriptions (in the sense of system analysis) as an auxiliary instrument for the experiments presented.

The research approach is intended to be design-oriented in accordance with the Design-Science-Research Methodology (DSRM) [16]. Thus, the second section provides the foundation of multi-site ANN simulation system construction from which requirements are derived that need to be reflected by the prototype. The third section justifies the concrete requirements for the global, neuronally instructed production network having multiple production facilities. The design artifact is then presented in the fourth section. Its usefulness will be demonstrated with the aid of experiments in section five. It issues how to examine the effects of ANN activation rates and cycles on production routines and clarifies how to intervene by management. In section six, it will be evaluated inhowfar the prototype design is suitable to enhance multi-site ANN-based CPPS. The insights are concluded in the last section.

2 Theoretical Foundation

Underlying concepts for the research presented here refer to the characterization of neuronally constructed systems (first sub-section) and the engineering of ANN-based cyber-physical production systems. The tool of system analysis and corresponding states characteristics that are commonly required to describe periodicity are specified in sub-section three, so that typical production situations can be characterized thereafter for the design of experiments.

2.1 Neuronal System Modeling and Artificial Knowledge Transfers

Artificial Knowledge Transfers. A knowledge transfer can be interpreted as conversion of different types of knowledge being bound to various kinds of knowledge carriers [17]. While the first form of knowledge refers to well documentable *explicit knowledge* [18], that can be handed among any kind of process participant easily (e.g. a book, data file or pixel information), the second form of knowledge is hard to document as it is knowledge-bearer-bound (e.g. experience). It is referred to as *tacit knowledge* [18] and can be found at human level as well as AI-based system level [15]. Among further interpretations, this knowledge can be interpreted as *neuronal pattern* consisting of a sequence of neural activations [15], which either can be found in the human brain on a biological level or they can be generated by virtually simulated brains based on artificial neural networks [19].

Neuronal System Modeling. By modeling neuronal patterns, e.g. with the aid of the Neuronal Modeling and Description Language (short: NMDL) [20], the following is enabled [13]: Either the activity of ANN-based systems can become transparent and made explainable as *artificial knowledge transfers* since the neural injection of explicit knowledge in ANN becomes clear and artificial knowledge objects are identified automatically (activation data-centered approach). Here, the processual behavior of ANN-based systems evolves due to unknown artificial knowledge transfers. Alternatively, AI-based systems can be transparently constructed and algorithmically interpreted (AI system engineering approach). Here, ANN structures follow predefined artificial knowledge transfers. In hybrid approaches, data-centered and engineering approaches can meet to enable the debugging of ANN systems: An evolving procedural behavior and predefined artificial knowledge transfers can be compared and fed back to real-world requirements. However, these approaches have been demonstrated in organization-wide interwoven

ANN-based systems which have had the same activation rates and start times [13].

Interim-Conclusion. Although ANN-based systems and respective artificial knowledge flows have been demonstrated at organization-wide levels, there is no research about interacting ANN-based systems that follow different activation rates and activation cycles. So far, neuronal modeled systems have been interwoven and activated as one system only, which is equivalent to one artificial brain. A research gap becomes apparent, here.

2.2 ANN-based Cyber-Physical Production Systems

Cyber-Physical Systems. Following Ashton [22], the physical meaning of classical production components is enhanced by embedded systems with structures similar to the Internet such that their physical meaning is supplemented by a virtual representation. Since those computational elements are collaborating to control their respective physical and virtual entities, they are hereinafter referred to as cyber-physical systems (CPS) [23]. According to their schematic structure [24], they provide the following: At least one *communicator* realizes the connection to other CPSs using internet protocols, e.g. for exchanging AI knowledge bases. *Sensors* perceive data from the environment and a CPS generates an understanding of its preferably certain states within the environment (e.g. by AI-based recognition). *Actuators* carry out the interactions with the physical environment so that a feedback loop can be closed, such as by AI generated instructions. *Processors* realize beside other tasks the decisions of the CPS. Here, different kinds of AI-based and non-AI-based decision strategies can coexist in one CPS to follow its strategy autonomously.

Cyber-Physical Production Systems. However, connecting several CPS to one Cyber-Physical Production Systems (CPPS) [7], each CPS in the production setting possesses individual abilities to act with, or perceive information from the environment and its surrounding CPS, which is more than simply receiving messages via its communication channels. Based on its location, individual limitations restrict its actions and time dependent states (e.g. their current production phase) influence its availability to interact with other CPS and realize production routines in cooperation. Facing the complexity of Industry 4.0 capably CPPS, a conceptual design of worldwide distributed CPPS are provided by Bender et al. [12]. However, the corresponding simulation realization has not been realized, yet.

ANN-based CPPS. Interwoven and by ANN instructed cognitive production networks of four different CPS types (one robot arm, two feeder, one conveyor) already have been realized in organization-wide context [13]. These lead to productive routines and realized cost savings and waste reduction for instance. However, these were located at one production facility, realized productions of one company and consisted of CPS purchased from vendor only.

Interim-Conclusion. Although conceptual ideas and fragments are available for worldwide CPPS systems on the one hand and ANN-instructed CPPS on the other hand, a multi-site CPPS that is based on ANN instructions or rather global, neuronally instructed production chains having multiple production facilities have not been realized, yet. A research gap becomes apparent, here.

2.3 System Analysis and System States

System Analysis. System analysis can be described as a systematic method for the model-based analysis of complex objects of investigation [25]. Here, the structure as well as the external and internal functionalities of an object of investigation (OoI) and its components are examined and evaluated in order to define requirements for a solution design. In this research, the OoI refers to ANN-based cognitive production networks of neuronally instructed production chains spanning multiple production facilities (cf. section 2.2) and respective neuronal knowledge patterns (cf. section 2.1) as well as the ANN-based induced production behavior. Particularly in cases of phenomena based on complex mechanisms, where the causes of phenomena were not based on isolated causal chains or relationships between a few variables (here analytical methods lead to great success), system analysis shows strengths with its consideration of system elements in an interdependent context [26]. Typically, examples refer to in growth and equilibrium processes, meshed control loops, complex decision sequences or socio-cultural development processes.

State Characterization. With the aid of *chaos theory*, system analyses e.g. intends to describe *periodicity* of dynamic systems. Intuitively, the state of a system describes enough about the system to determine its future behavior in the absence of any disregarded influences affecting the system. From particular interest is the state of *equilibrium*, which means that the behavior of dynamic systems does not change over time without external influence [27]. In this research, each production site is considered as dynamic ANN-based system (due to recurrent ANN structures and humans in the loop), which will be examined as combined dynamic system of interwoven cognitive production networks inhowfar their activation will result in a *joint equilibrium*. In this context, the joint equilibrium means that their production behavior does not change over time without external influence and a production routine evolves. It will be examined inhowfar this equilibrium is productive in regard with rejected goods, waste, time consumed, etc., too. By now, as Fig. 1 shows, the following kinds of equilibrium-related state descriptions are distinguished for dynamic systems [27–29]:

a) Systems are *unstable* or *chaotic* if respective systems are deflected slightly and do not return to its original reference position, but the deflection increases. In this research, a deflection means a deviation from the originally learned ANN tasks and corresponding artificial knowledge flows that evolve a working production routine at reference activation rates and cycles. Often, the systems' respective knowledge flows reinforce themselves. This self-reinforcement can be referred to as positive feedback and leads to apparently *arbitrary* changes in the production context simulated.
b) A dynamic system is *stable* if the system returns to its initial state after a deflection or fault. For instance, although the production network is faced with deflected activation types, the intended production process can be realized due to efficient knowledge flows among ANN-based systems.

c) The system is *labile* if it changes state at the slightest disturbance. For instance, any kind of activation type change results in alternative production processes.
d) The dynamic system is *metastable* if it returns to a more stable equilibrium state after a sufficiently large deflection or disturbance. For instance, the production network comes up with improved production routines if different activation types are used.
e) If a metastable system has two equilibrium states, it is also referred to as *bistable*. Many dynamical systems exhibit the coexistence of several stable states, which is also known as *multistability* [30].
f) The dynamic system is *indifferent stable* if it comes to rest in a new state after every deflection or disturbance. For instance, the production network comes up with alternative production routines if different activation types are used. It needs to be questioned if the alternative is productive, too.

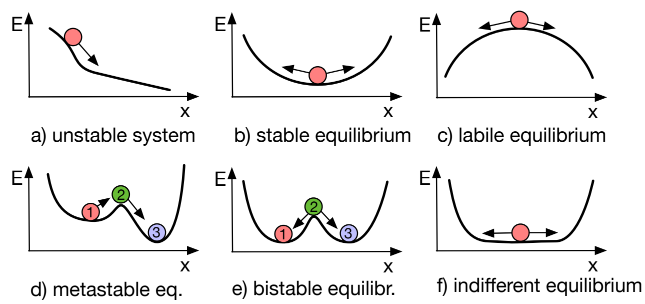

Fig. 1: The equilibrium-related state descriptions of dynamic systems.

Since the different forms of equilibrium (stable, labile, metastable, bistable, multistable and indifferent) can be related to a production behavior recurrent at regular interval, producing workpieces periodically in routines as intended intended, these are referred to as *periodic* systems from hereon and differentiated from *chaotic* systems.

Stability in Neuron Dynamics. Biological and artificial neuronal networks have been studied in regard with stability since decades. For instance, it is supposed that the biological origin of bistable visual perception draws back to neuron cells activity, which induces switches between different perception states [31, 32]. On the level of single neurons, multistability is represented by the coexistence of basic firing patterns, like silence, spiking, regular, and chaotic bursting [33]. On the level of group of neurons, the physiology of neural systems has been examined: Here, dynamical concepts were focused, such as time delay [34], phase locking patterns [35], or delayed recurrent neural loops [36]. However, studies mostly refer to mathematical analyses, but not system analysis methods and by ANN-instructed machines in simulations. Further, they do not cover decentralized AI realization strategies and corresponding Industry 4.0 capable infrastructures.

Interim-Conclusion. Per se, there is no state description that enables the characterization of combined dynamic systems which considers different kinds of ANN activation rates and activation cycles. System analyses enables the individual analysis of any kind of sub-system but not the activation type-related state characterization so far. For instance, the system-specific ANN activation rates can have *coupled* or *decoupled* starting times. Further, from an analytical perspective, they can refer to the *same* or *different* rates, while the latter can refer to *divisible* versus *indivisible* rates, *duplicable* versus *unduplicable* or *irregular* rates. Although simulation of spiking neural networks have been analyzed in regard with balancing states, the activation type related evolving behavior of ANN-based systems, such as in production contexts, has not been focused, yet. A research gap becomes apparent, here.

3 Objectives of a Solution

Following the DSRM [16], requirements of a prototype are defined before the design of artifacts is carried out. The requirements of Tab. 1 have been synthesized from literature and served as the design maxims for the multi-site ANN simulator design. Further, they have functioned as quality gates for artifacts presented here and they can stand as quality gates for subsequent research.

Table 1: Requirement collection.

ID	Requirement Description
1.	**Req.** *(Digitization)*: The production machines of a production site need to be digitized so that a Digital Twins is created per machine [37]. Analog electric signals need to be transformed to digital signals, so that these can be processed by computers embedded at the machines and routing them through standard output sockets [38].
2.	**Req.** *(IoT-Integration)*: The production machines as technical device needs to be integrated in the IoT structure [39], so that a communication by the machines and further dialog partners can be realized. These partners can refer to further production machines, alternative devices and human process participants.
3.	**Req.** *(CPS-Capabilities)*: The production machine needs to provide components of sensors, actuators, processors and communicators, so that CPS capabilities can be realized [7].
4.	**Req.** *(AI-based Instruction)*: As the machine design has not a purpose in itself, it needs to follow a production routine, so that a workpiece carrier is constructed step by step. In accordance with the AI-based instruction mechanism [13], the machine's controlling is not realized by static software code but adaptive, flexible and efficient AI instructions.
5.	**Req.** *(AI Infrastructure)*: As the machines of each production site are instructed by AI [9], the machines are integrated in an AI supportive infrastructure. In accordance with AI architectures [40], the machines correspond to the shop floor level (*cps level*) representing nodes with low computing power for AI processing. More powerful computing nodes for fast AI processing can be at the *local cloud level*. The most powerful and costly computing nodes can be rent ad-hoc via AI cloud services (*public cloud level*). Example hardware services are provided by Amazon, Google, Microsoft, etc.
6.	**Req.** *(AI Platform)*: Since individual machines and productions sites shall be considered as production network, these need to be integrated with one end-to-end platform for cyber-physical systems, that enables the efficient application of knowledge of ANN [21]. For this, it needs to enable the flexible, node-independent (a) situational ANN application, (b) ANN training and validation as well as (c) ANN refinement, etc., which is realized as Over-The-Air deployment. Further, arbitrary programming libraries, such as TensorFlow or PyBrain, need to be provided, so that specialized AI functions are supported. Lastly, it needs to support AI experiments, which means the parameterized machine initialization having a machine-specific selective *AI activation rate* as well as a selective *AI activation cycle*.

4 Design

In regard with the DSRM [16], the design presents research problem solution in form of artifacts, which will demonstrate their usefulness in the demonstration section. As was identified in section two, these artifacts refer to (a) the production site design, (b) the scenario design, (c) the task design, (d) the AI system design, (e) the experiment design and, (f) the simulation system design. Each will be presented in an individual sub-section.

Since the production sites were ought to be instructed by AI and the *Concept of Neuronal Modeling* [13], the individual artifacts were designed with the aid of the Neuronal Modeling and Description Language (short: NMDL) from [20].

4.1 Production Site Design

In the beginning, the hardware for the experimental investigation has been designed and set up. Therefore, the distributed production facilities and machine interactions are designed. The result is the physical construction of a distributed Industry 4.0 production plant structure that can simulate global production chains. According to Fig. 2, this consists of the following production facilities: (1) an AI-based logistics center for shipping goods in Pretoria, (2) an AI-based logistics center for receiving goods in Bochum and (3) further production facilities for AI-based goods processing in Potsdam. Based on the NMDL's *Organizational Overview*, in the figure, one can see the individual organizational units and its technical sub-elements. So, the technical designation of physical devices and their composition and use in the scenario design is prepared.

On the physical production structure shown in the figure, the AiRaci-based system *AiRaci-CPS1* with the human worker named *AiRaci-Worker1* simulates the first production facility for dispatching goods. The second production site simulates the AiRaci-based system *AiRaci-CPS2* with the human worker *AiRaci-Worker2* for receiving goods. The production facilities for further goods processing simulate the LEGO-based system structure of *AiLego-CPS1*, *AiLego-CPS2*, *AiLego-CPS3* and *AiLego-CPS4* with the human worker named *AiLego-Worker1* as well as the fischertechnik-based system structure of *AiFischertechnik-CPS1* to *AiFischertechnik-CPS7* with the human worker named *AiFischertechnik-Worker1*. The workpiece carrier called *AiRaci-CPS3* can now be passed back and forth between the AI-based production facilities, e.g. with the help of the short and long conveyors or the human letter carrier (see Postman in the figure). Each production facility continues to produce the workpiece carrier step by step according to the designed scenario.

The corresponding physical devices can be seen in Fig. 3. For replicating these kinds of physical production components, please let us know.

4.2 Scenario Design

For driving the physical production machines presented in section 4.1, the software for the experimental investigation as well the implementation of production sequences has been realized. First, scenarios for global production chains are designed and relevant parameters are operationalized. The *ProcessView* of the NMDL represents the underlying production processes and the interaction of the physical production facilities (see Fig. 4) introduced in Fig. 2.

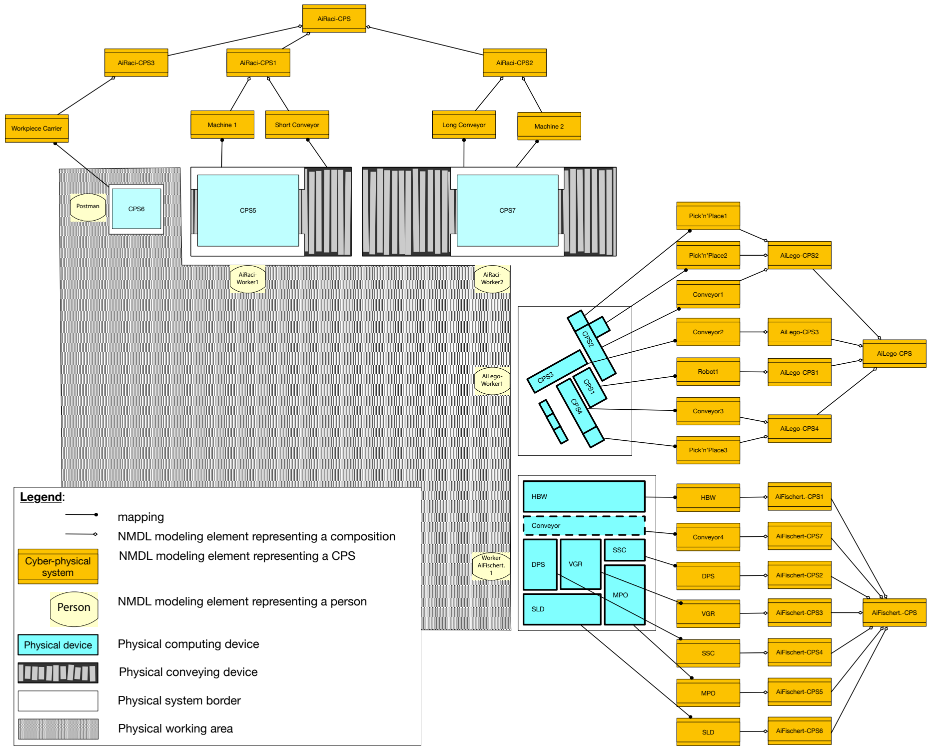

Fig. 2: The Organizational Overview of NMDL and layout of multi-site ANN-based cyber-physical production systems.

The figure shows that fruit is first produced in the first AiRaci production facility. It is then refined in the second AiRaci production facility. The refined fruit is then processed into jam in the fischertechnik production facility. In the fourth Lego production facility, the marmalade is packaged and marmalade jars are labeled so that they can be sold in retail stores. The scenario modeling of an error-free production chain thus represents a process instance of sequential production tasks with four production facilities.

Since all systems are modeled with the neural process design tool CoNM and are instructed based on AI, the focus is on observing the synchronization and activation cycles of the two AiRaci production facilities, which are at the beginning of the production chain. If neuronal information is already lost here in the first production facilities due to inefficient synchronization and activation cycles, this has an impact on subsequent cognitive production systems. These two production sites are therefore the focus of the investigation and Fig. 13 shows the detailed sequence of these two production sites.

The figure shows the time at which an AI-instructed CPS must become active in order to perform the production task shown in green. This relates to activation cycles and rates, which go hand in hand: In the interaction of various AI-instructed CPS, a workpiece carrier is thus produced piece by piece. At the same time, however, the CPSs involved

Fig. 3: The physical layout of multi-site ANN-based cyber-physical production systems.

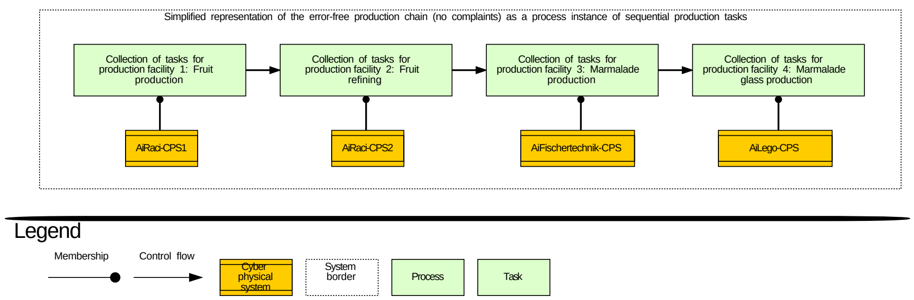

Fig. 4: The ProcessView of NMDL on the production process of multi-site ANN.

must also be able to implement idle behavior - for example, no machine may become active and perform its respective activities to produce goods if no materials or workpiece carriers are available. Fig. 12 shows the paused tasks for the relevant systems of the two AiRaci production sites, provided that the entire production chain and therefore both production sites are not supposed to do anything and are paused.

The focus of the research is therefore now on the disruption state of production, where the activation cycles and rates of two production facilities do not go hand in hand and, for example, *Machine1* of the first production facility produces workpieces faster and sends them to *Machine2* of the second production facility than the second production facility can process or the second production facility slows down the first.

The following parameters to be operationalized are therefore determined for the two machines named *Machine1* of the first production facility and *Machine2* of the second production facility: On the one hand, the start times of the cyclical AI deployments as *activation cycle* according to the respective tasks in the characteristics a) coupled and b) decoupled (delayed / premature). On the other hand, the repetition duration of the AI applications as *activation rate* according to the respective, same tasks in the specifications a) equal b) different.

4.3 Task Design

For clarifying the respective AI tasks of Fig. 13 called ”AI-based image classification and documentation of the result on the hard disk”, the NMDL’s ActivityView specifies the following two:

First, an AI-based classification task that relates to the analysis of fruit images of the varieties a) bananas, b) oranges and c) apples, which contain m pixels in the x-axis and n pixels in the y-axis and have RGB values. Fig. 5 shows the task of the two AI-based machines and conceptualizes the incoming data to be collected and the outgoing data to be generated in the scenarios determined.

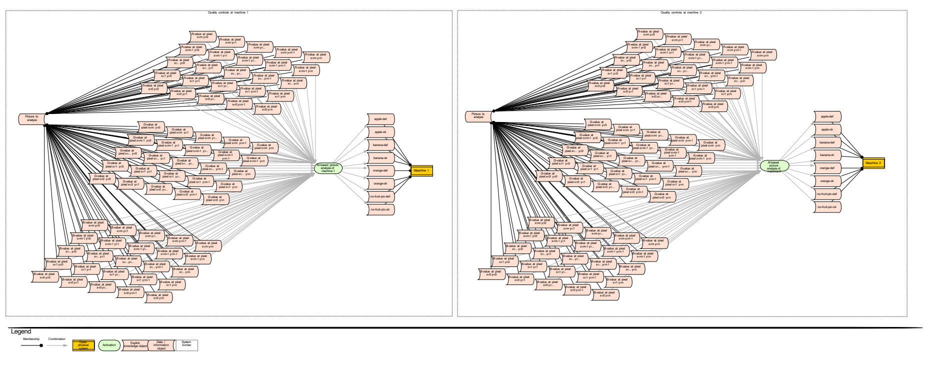

Fig. 5: The ActivityView of NMDL on AI-based picture classification of multi-site ANN.

The figure shows that the RGB values of each pixel of the image to be analyzed serve as input values in the scenarios and the class combinations of the three types of fruit (bananas, oranges, apples) with the quality levels (defective and ok) must be generated as outgoing values. It must also be possible to pause the two machines, which is achieved using the two ”no-fruit-pic” classes.

Since the workpiece carrier, which represents the respective fruit and represents image material, is transported back and forth between *Machine1* and *Machine2* in the scenarios by means of the short and long transport conveyor systems, Fig. 6 clarifies the second AI-based classification task that relates to the analysis of transport situations. It shows the modeling of the corresponding two AI-based transport tasks for the short conveyor bench on the left and the long conveyor belt on the right.

The figure shows which incoming sensor values from the respective transport system are used by the neural structure used here to generate the outgoing neural instructions for a) a transport movement from left to right, b) a transport movement from right to left and c) a pause. Furthermore, in both systems, the fourth neuron d) indicates an alarm situation and the fifth neuron e) indicates a complaint.

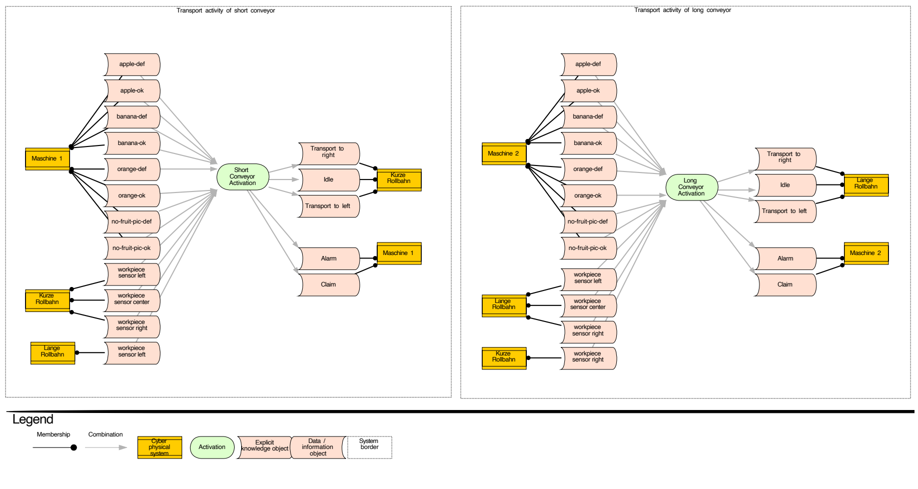

Fig. 6: The NMDL's ActivityView on AI-based transport classification.

4.4 AI Application Design

First of all, the distributed production facilities created in section 4.1 and situated in scenarios created in section 4.2 are operated in normal mode and data is collected. For this purpose, a synthetic data set was compiled, which corresponds to the conceptualization of the AI-based image analysis according to the modeling and limit scenarios (including worst-case scenarios) and is based on the (1) AI-based image classification and the shown in Fig. 5 and (2) AI-based transport classification (see Fig. 6). These datasets can be found in the repository:

- Training material for AI image classification, which is based on the collection by Kalluri (2018): *https://github.com/MarcusGrum/AI-CPS/tree/main/data/fruits-fresh-and-rotten-fruits-dataset*
- Training material for the AI transport classification of CPS1: *https://github.com/MarcusGrum/AI-CPS/blob/main/documentation/experiment05/datasets/Cps1_TrainDs.csv*
- Training material for the AI transport classification of CPS2: *https://github.com/MarcusGrum/AI-CPS/blob/main/documentation/experiment05/datasets/Cps2_TrainDs.csv*

This is followed by training to create models for the respective Industrie 4.0 production systems. The result is neural models for the machines of the distributed Industrie 4.0 production facilities, which can instruct them with neural activations based on AI-based image recognition in such a way that global production chains are realized. By comparing the incoming and outgoing values shown in Fig. 5 and Fig. 6, the interfaces between individual production facilities that are relevant for the production chain can be recognized by the names of the same name. The neuronal structures of the AI models responsible for AI-based image analysis are shown schematically in Fig. 7.

Since the neural structures were implemented with the TensorFlow programming library, the specific technical names of this programming library can be found in the

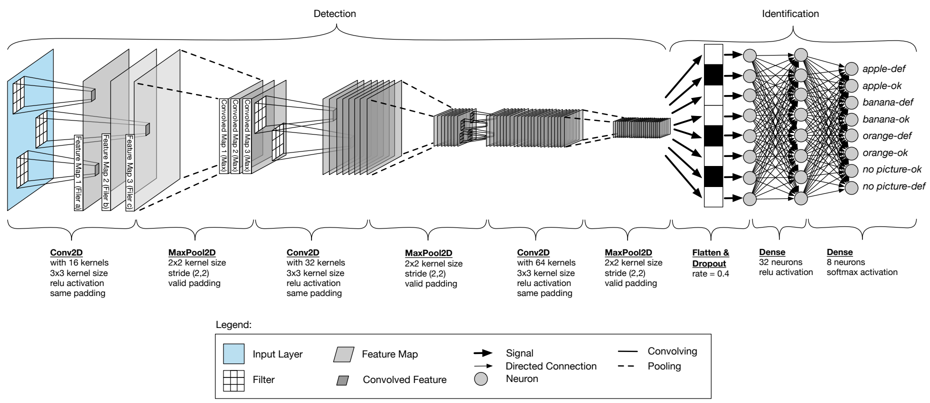

Fig. 7: The NeuronView of NMDL clarifies the AI-based picture classification of multi-site ANN.

figure under the respective neural layer. The trained models for AI-based image analysis have been made available in the Dockerhub as a ”knowledgebase”:

– Relevant knowledge bases: *https://hub.docker.com/u/marcusgrum*

The neural architecture of the two transport conveyor systems has a neural connection to the respective upstream AI image analysis and is shown in Fig. 8. For this purpose, the PyBrain programming library was extended and used to implement the AI transport analysis. The extension has also been made available:

– Extended PyBrain library: *https://github.com/MarcusGrum/pybrain*

A comparison with the conceptual scenario planning shows that the incoming neuronal values from Fig. 6 match the input neurons in Fig. 8 and that the scenarios are therefore implemented and trained at the neuronal level.

The neuronal models are used here as ANN apply requests. The mechanism responsible for this is also prepared in the repository:

– ANN request manager:
https://github.com/MarcusGrum/AI-CPS/blob/main/code/annRequests_.../apply_annSolution.py

This means that the use of a trained AI model for image recognition on the machines named *Machine1* and *Machine2* and the associated conveyor belt systems named *ShortConveyor* and *LongConveyor* is prepared and only needs to be called up in the operationalized parameter configurations in accordance with the experimental investigation designed in the next section.

4.5 Experiment Design

For planning and carrying out the experimental investigations so that production facilities can be operated with the same/different activation cycles/rates and initial hypotheses can

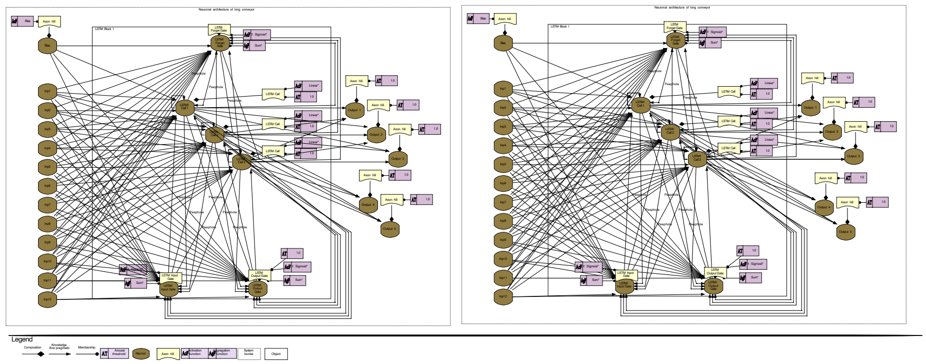

Fig. 8: The NMDL's NeuronView on AI-based transport classification of multi-site ANN.

be answered, the distributed production facilities are operated using neural instructions and performance data is collected. Fig. 9 shows the design of experiments (DoE), also known as experimental design, focusing on the planning of each task as follows: Each planned task aims to describe and explain the variation of information under conditions that are thought to reflect the variation.

		Activation rates	
		same rates	different rates
Activation cycles	coupled /synchronous cycles	H1	H3
	decoupled /asynchronous cycles	H2	H4

Fig. 9: The experiment variants of multi-site ANN.

The figure shows that the planned experiments differentiate the activation cycles in the two variants "coupled" or "synchronous" and "uncoupled" or "unsynchronized" as well as the activation rates in the two variants "equal" and "different", resulting in a 2x2 matrix with four experiment variants. Each variant or task serves to test one of the four initial hypotheses, so that the general task can be formulated as follows:

– General experiment task:
  An AI-based production chain with at least two neuronally instructed production facilities is to be operated, whereby the activation cycles of the production facilities

are varied with regard to the activation cycle and the activation rates and the KNN-based knowledge bases used are retained and confronted with different experiment variants in such a way that any faults that may occur due to different activation rates and cycles in production operations can be investigated.

At the same time as realizing the experimental task of operating the described production facilities using neural instructions and simulated production chains, quality defects in production products and the automated documentation of production times are determined. The result is the collection of data from simulated production chains in distributed Industry 4.0 production facilities, which can be examined with regard to fault-free operation.

Assumptions: If a malfunction occurs during proper operation, it is assumed that the workpiece to be produced suffers a quality defect and must be rejected (Assumption 1). The following is also assumed:

- Assumption 2: The reference scenario and therefore the basis for training is the scenario of hypothesis 1.
- Assumption 3: Fruit workpieces are fed into the production system by the letter carrier as soon as the long conveyor system has taken over the workpiece from the short conveyor system. This ensures that there are always enough orders in the production system, but that two workpieces with competing transport movements are not placed on one and the same conveyor element.
- Assumption 4: The transports via the conveyor systems always take one simulation minute (including the calculation times of the associated neural activations for image and transport). This is particularly important with regard to shorter activation questions (e.g. ID3 of Fig. 14), as neuronal activation cannot change the physical processes in the real world.
- Assumption 5: The respective total simulation time amounts to three simulation time states or simulation cycles.

The following interaction hypotheses shown in Fig. 14 and Fig. 15 were derived for the four experiment variants shown in Fig. 9, as they show the realistic and possible permutations of activation rates and cycles. These arise if a) activations are carried out early or late, b) activation rates are at regular intervals or multiples of each other, c) activation rates are at irregular intervals of each other or d) activation rates are completely variable in relation to each other.

The **system analysis** has shown that IDs 1-6 and 9-12 result in a periodic dynamic system state and IDs 7-8 and 13-14 result in a chaotic dynamic system state. It should be noted that the system state identified here (periodic or chaotic) says nothing about the disruptions or inefficiencies that arise in the production chain simulated here. However, since the analyses of neuronally induced behavior (presented in the demonstration section) showed that the two system states of dynamic systems (periodic and chaotic) do not allow sufficient differentiation for neuronal activation rates and cycles in the sense of common system analysis, more detailed, novel state descriptions were derived in the sense of a *musical rhythm analysis*. Using these novel **rhythmic state descriptions of dynamic systems**, the experimental tasks can now be clearly divided into distinguishable categories based on the type of activation cycle-activation rate combination determined in the respective experimental task, and the type of synchronization present can be described unambiguously. These are particularly helpful as category-specific disruption patterns could be identified for these and used to derive corrective management interventions, which will be described in detail later.

In particular, the following IDs are relevant for an initial investigation, as explained below:

- ID1: The activation of CPS1 and CPS2 is realized as it was originally planned and intended when the neural production chain was built, trained and installed.
- ID2: Either the activation of CPS2 is inadvertently delayed or CPS1 is inadvertently activated too early. For example, an AI request sent via the Internet has been lost and resending it requires more time and delays the activation of CPS2.
- ID3: CPS2 is activated several times even though the actual work, e.g. a transport, has not yet been completed. For example, an order that was sent via the Internet was inadvertently sent several times.
- ID9: CPS2 is activated with a time delay (delayed/early) and at several points in time, even though the actual work, e.g. a transport, has not yet been completed. A delay can result, for example, from a temporarily high workload for CPS2. Since CPS2 did not respond in time due to the high workload, AI requests were automatically sent multiple times.
- ID14: Probably the most realistic task setting because organizations probably do not synchronize production processes - CPS1 and CPS2 are activated as required by the subjective circumstances of a production site or as desired by production managers. This means, for example, the arbitrary activation of any CPS without having a view of efficient global production chains.

These IDs will be examined in more detail as part of a first examination, whereby further IDs are to be systematically investigated thereafter so that management interventions can be systematically identified. These are intended to eliminate disruptions in global, neuronally instructed production chains. Furthermore, the management interventions identified are to be tested immediately to be applied for, so that a catalog of interventions for the trouble-free operation of neuronally instructed global production chains for application-oriented research and practice is created.

4.6 Simulation Design

The implementation of the scenarios is based on a software substructure with which the hardware of the Industry 4.0 production systems from section 4.1 can be operated. This was prepared as a repository so that computing nodes or machines from different platform systems can be set up using the same software structure:

- Node-independent software structure: *https://github.com/MarcusGrum/AI-Lab*

Here, each machine is integrated as an MQTT client so that the respective AI deployment on *Machine1* and *Machine2* can be tracked throughout the entire production structure via a message broker and results are also available to other interested CPSs. Fig. 10 shows the possible communication structures schematically.

For example, *Machine1* communicates with other CPS of the first production facility via *MessageBroker1* and *Machine2* and other production facilities of the Lego-based and

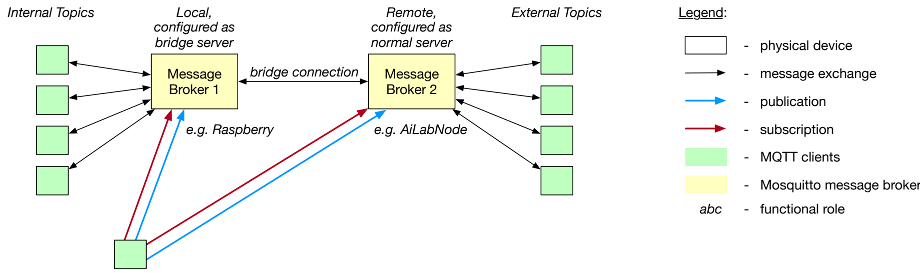

Fig. 10: The communication structure of multi-site ANN.

Fischertechnik-based production facilities via a *MessageBroker2*, which are connected to this communication exchange via a bridged connection. In addition, the messages exchanged here can be intercepted so that times and results can be documented and used for analysis. This was prepared as a repository so that various computing nodes can implement the AI application:

- MessageBroker: *https://github.com/MarcusGrum/AI-CPS/tree/main/code/messageBroker*
- MessageClient: *https://github.com/MarcusGrum/AI-CPS/tree/main/code/messageClient*

In order to guarantee the cycles and activation rates visualized in Fig. 14 and Fig. 15 in the experiment considered here, a system-wide or cross-production site scheduling algorithm or controlling clock generator was implemented, which is integrated as an additional communication client in the communication structure shown in Fig. 10. By means of its documenting and controlling role, it ensures that activations are realized at the planned (calculated) simulation times and that results, which are distributed across the communication channels, are also documented. This has been made available in the repository:

- Experiment: *https://github.com/MarcusGrum/AI-CPS/blob/main/code/experiments/experiment05.py*

In this simulation system, the communication behavior of the participating physical and virtual simulation devices shown in Fig. 11 is thus established, with the latter ensuring the correct timing of the respective experiment scenario.

5 Demonstration

In accordance with design-oriented research [16], the application of designed artifacts demonstrates their use, so that one is able to evaluate if the original research problem can be overcome. In this research context, the scenarios created in section 4.2 that follow the novel kinds of *rhythmic state descriptions of dynamic systems* (see section 4.5) are simulated by the simulation system designed in section 4.6. This provides production facilities (section 4.1) implementing the tasks designed in section 4.3 and instructed by AI application systems presented in section 4.4.

Since all these sub-artifacts are brought together by one new type of device simulating global production chains being instructed by ANNs, the experiments draw attention to the interplay of different types of ANN activation rates and cycles in multi-site CPPS.

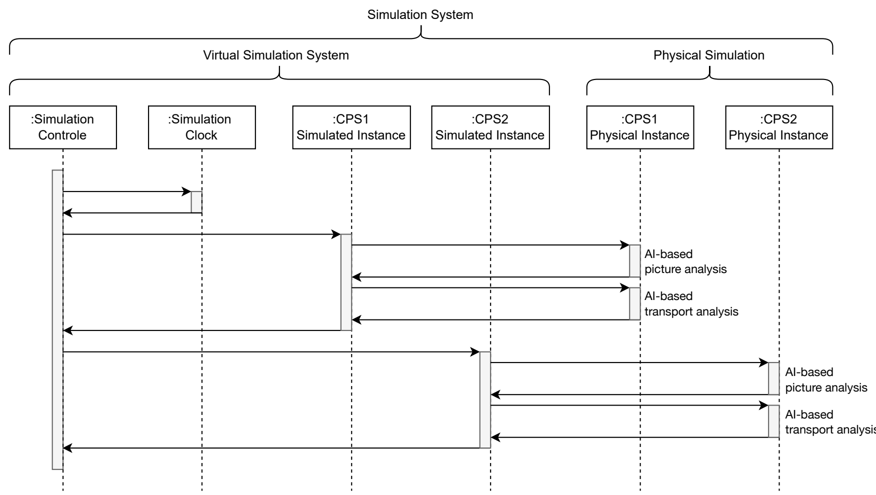

Fig. 11: The communication flow of the joint simulation system.

5.1 Experiment 1 - ID1

During the execution of the simulated production scenario with the ID1, the behavior described below was observed (behavior description). The activity analysis of the associated neuronal structures provides possible behavioral analyses and explanations:

1st cycle: M1 recognizes the 1st fruit delivery of good quality and the short conveyor belt transports this fruit delivery to its right side. Meanwhile, M2 recognizes a ”no fruit” picture (cf. ”no-fruit pic” in Fig. 8), as the position detected by a camera does not show a fruit delivery or is empty. M2 therefore remains idle or M2 is paused.

2nd cycle: M1 must pause because the fruit delivery has not yet been taken over by CPS2 or its conveyor belt system and is still on the short conveyor belt system of CPS1. As the position for image analysis is unoccupied, M1 recognizes the image ”no fruit” at the time of activation. At the same time, M2 recognizes the image ”no fruit”, as its position for image analysis is still not occupied and transports the fruit from the left side to the image analysis at M2 using the long conveyor belt system.

3rd cycle: M1 recognizes the second fruit of good quality, which has now been fed in by the letter carrier. The short conveyor belt thus transports the fruit delivery from the image analysis position to the right-hand side of the short conveyor belt system (transfer position to the long conveyor belt system). Meanwhile, M2 identifies the good quality fruit and the long conveyor belt transports the fruit delivery to the right to the transfer position to the connected Lego model system or the fischertechnik model system.

The performance analysis showed that the following key performance indicators (KPIs) could be collected in the simulated production scenario and in the experimental task with ID1:

- Fruit deliveries sent by the automated letter carrier at CPS1: 2
- Successful productions detected at CPS2: 1
- Production defects detected in the product: 0

- Completion of production compared to planning: on time

To achieve this performance, the individual system analysis of the experimental task with ID1 shows the following neuron-induced activities:

- 3 fruit analyses performed, of which
  - fruit analyses performed for M1: 2
  - Fruit analyses performed for M2: 1
- 3 "no-fruit" analyses performed, of which
  - "No-fruit" analyses performed at M1: 1
  - "No-fruit" analyses performed for M2: 2
- 2 pause instructions carried out, of which
  - pause instructions carried out for the short conveyor system: 1
  - pause instructions carried out on the long conveyor system: 1
- 4 transportation instructions carried out, of which
  - transport instructions carried out on the short conveyor system: 2
  - Transport instructions carried out on the long conveyor system: 2

5.2 Experiment 2 - ID2

In the simulated production scenario with the ID2, the behavior described below was observed (behavior description) and the following behavioral explanations were derived based on the behavior analysis:

1st cycle: M1 recognizes the 1st fruit delivery of good quality and the short conveyor belt transports this fruit delivery to its right-hand side. Meanwhile, M2 recognizes a "no fruit" picture (cf. "no-fruit pic" in Fig. 8), as the position detected by a camera does not show a fruit delivery or is empty. M2 therefore remains idle or M2 is paused.

2nd cycle: M1 must pause because the fruit delivery has not yet been taken over by CPS2 or its conveyor belt system and is still on the short conveyor belt system of CPS1. As the position for image analysis is also vacant here (as with ID1), M1 recognizes the image "no fruit" at the time of activation. At the same time, M2 recognizes the image "no fruit" as its position for image analysis is still not occupied and transports the fruit from the left side to the image analysis at M2 using the long conveyor belt system.

3rd cycle: M1 has to pause again (and unnecessarily) because the processing phase of CPS2 has not yet been completed due to the delayed processing start or M2 has not yet released the fruit delivery. M1 therefore recognizes the "no fruit" screen again. When the task of the previous processing cycle of CPS2 is completed, M2 then identifies good quality fruit in the connected cycle and the long conveyor belt transports this fruit delivery to its transfer position in the Lego and fischertechnik miniature world on its right-hand side.

The performance analysis showed that the following key performance indicators (KPIs) could be collected in the simulated production scenario and in the experimental task with ID2:

- Fruit deliveries sent by the automated letter carrier at CPS1: 1
- Successful productions detected at CPS2: 1
- Production defects detected in the product: 0
- Completion of production compared to planning: delayed

To achieve this performance, the individual system analysis of the experimental task with ID2 shows the following neuron-induced activities:

- 2 fruit analyses performed, of which
  - fruit analyses performed for M1: 1

- Fruit analyses performed for M2: 1
- 4 ”no-fruit” analyses performed, of which
  - ”No-fruit” analyses performed for M1: 2
  - ”No-fruit” analyses performed for M2: 2
- 3 pause instructions carried out, of which
  - pause instructions carried out for the short conveyor system: 2
  - pause instructions carried out on the long conveyor system: 1
- 3 transportation instructions carried out, of which
  - transport instructions carried out on the short conveyor system: 1
  - Transport instructions carried out on the long conveyor system: 2

5.3 Experiment 3 - ID3

In the third production scenario (experimental task with the ID3), the following behavior was observed and behavioral analysis and explanations were identified:

1st cycle: M1 recognizes the 1st fruit delivery of good quality and the short conveyor transports this fruit delivery to its right side. Meanwhile, M2 recognizes a ”no fruit” image for three iterations (cf. ”no-fruit pic” in Fig. 8), as the position recorded with a camera does not show a fruit delivery or is empty. This means that M2 remains idle for three iterations or M2 is paused.

2nd cycle: M1 must pause because the fruit delivery has not yet been taken over by CPS2 or its conveyor belt system and is still on the short conveyor belt system of CPS1. As the position for image analysis is occupied during this time, M1 recognizes the image ”no fruit” at the time of activation. At the same time, M2 recognizes the image ”no fruit” in the first iteration, as its position for image analysis is still not occupied, and starts the fruit transport from the left side to the image analysis position at M2 using the long conveyor belt system. In two further iterations, M2 recognizes that there is no fruit and instructs the system to idle or pause, although the transport of the workpiece to M2 has not yet been completed. This is because the underlying CNN has not learned to continue the transport for a further two iterations and so, for example, the workpiece is lost between the sensory perception of the CPS. As the idle command overwrites the current transport process, the workpiece has to be sorted out manually. This corresponds to a malfunction due to the multiple activation, which could have been avoided and is unnecessary.

3rd cycle: M1 recognizes the second fruit of good quality, which has now been fed in by the letter carrier. The short conveyor belt thus transports the fruit delivery from the image analysis position to the right-hand side of the short conveyor belt system (transfer position to the long conveyor belt system). Meanwhile, M2 identifies the ”no fruit” image in three iterations and the long conveyor belt pauses for three iterations.

The performance analysis showed that the following key performance indicators (KPIs) could be collected in the simulated production scenario and in the experimental task with ID3:

- Fruit deliveries sent by the automated letter carrier at CPS1: 2
- Successful productions detected at CPS2: 0
- Production defects detected in the product: 1
- Completion of production compared to planning: no finalization

To achieve this performance, the individual system analysis of the experimental task with ID3 shows the following neuron-induced activities:

- 2 fruit analyses performed, of which
  - fruit analyses performed for M1: 2
  - Fruit analyses performed for M2: 0
- 10 ”no-fruit” analyses performed, of which
  - ”No-fruit” analyses performed for M1: 1
  - ”No-fruit” analyses performed for M2: 9
- 9 pause instructions carried out, of which
  - pause instructions carried out for the short conveyor system: 1
  - pause instructions carried out on the long conveyor system: 8
- 3 transportation instructions carried out, of which
  - transport instructions carried out on the short conveyor system: 2
  - Transport instructions carried out on the long conveyor system: 1

5.4 Experiment 4 - ID9

The simulation of the production scenario with the ID9 led to a behavior description and behavior analysis/explanation approach:

1st cycle: M1 recognizes the 1st fruit delivery of good quality and the short conveyor transports this fruit delivery to its right side. Meanwhile, M2 recognizes a ”no fruit” image for three iterations (cf. ”no-fruit pic” in Fig. 8), as the position recorded with a camera does not show a fruit delivery or is empty. M2 therefore remains idle for three iterations or M2 is paused.

2nd cycle: M1 has to pause because the fruit delivery has not yet been taken over by CPS2 or its conveyor belt system and is still on the short conveyor belt system of CPS1. As the position for image analysis was occupied, M1 recognizes the image ”no fruit” at the time of activation. At the same time, M2 recognizes the image ”no fruit” in the first iteration, as its position for image analysis is still not occupied, and starts the fruit transport from the left side to the image analysis position at M2 using the long conveyor belt system in the first iteration. In two further iterations, M2 recognizes that there is no fruit and instructs the system to idle or pause, even though the transport of the workpiece to M2 has not yet been completed. This is because the underlying CNN has not learned to continue the transport for a further two iterations and so, for example, the workpiece is lost between the sensory perception of the CPS. As the idle command overwrites the ongoing transport process, the workpiece has to be sorted out manually - a disruption due to the multiple activation (even if delayed) that could have been avoided and is unnecessary.

3rd cycle: M1 recognizes the second fruit of good quality, which has now been fed in by the letter carrier. The short conveyor belt thus transports the fruit delivery from the image analysis position to the right-hand side of the short conveyor belt system (transfer position to the long conveyor belt system). Meanwhile, M2 identifies the ”no fruit” image in three iterations and the long conveyor belt pauses for three iterations.

The performance analysis showed that the following key performance indicators (KPIs) could be collected in the simulated production scenario and in the experimental task with ID9:

- Fruit deliveries sent by the automated letter carrier at CPS1: 2
- Successful productions detected at CPS2: 0
- Production defects detected in the product: 1
- Completion of production compared to plan: no completion, late

To achieve this performance, the individual system analysis of the experimental task with ID9 shows the following neuron-induced activities:
- 2 fruit analyses performed, of which
  - fruit analyses performed for M1: 2
  - Fruit analyses performed for M2: 0
- 10 ”no-fruit” analyses performed, of which
  - ”No-fruit” analyses performed for M1: 1
  - ”No-fruit” analyses performed for M2: 9
- 9 pause instructions carried out, of which
  - pause instructions carried out for the short conveyor system: 1
  - pause instructions carried out on the long conveyor system: 8
- 3 transportation instructions carried out, of which
  - transport instructions carried out on the short conveyor system: 2
  - Transport instructions carried out on the long conveyor system: 1

5.5 Experiment 5 - ID14

When running the simulated production scenario with the ID14, the observed behavior could be analyzed and explained as described below (behavior analysis and explanation approaches):

1st cycle: M1 recognizes the 1st fruit delivery of good quality and the short conveyor belt starts transporting the fruit delivery to its right side. Meanwhile, M2 recognizes a ”no fruit” image for three iterations (cf. ”no-fruit pic” in Fig. 8), as the position detected with a camera does not show a fruit delivery or is empty. M2 therefore remains idle for three iterations or M2 pauses.

2nd cycle: M1 recognizes ”no fruit” image, as the fruit delivery is still on its way to the right side of the short conveyor belt system (transfer position to CPS2) and the image analysis position at M1 is empty. A pause is therefore instructed. The underlying ANN has not learned to continue the transport for intermediate iterations. This means, for example, that the workpiece is lost between the sensory perceptions of the CPS1. As the idle command overwrites the ongoing transport process of CPS1, the workpiece has to be sorted out manually (unnecessarily). Meanwhile, M2 recognizes the image ”no fruit” in three iterations and instructs idle or pause of the long conveyor belt system, as the transport of the workpiece to the right side of CPS1 has not yet been completed.

3rd cycle: M1 recognizes the second fruit of good quality, which has now been fed in by the letter carrier. CPS1 therefore starts transporting the fruit delivery using the short conveyor belt from the image analysis position at M1 to the right-hand side of the short conveyor belt system (transfer position to the long conveyor belt system). Meanwhile, M2 identifies the ”no fruit” image and starts the pause of the long conveyor belt system.

The performance analysis showed that the following key performance indicators (KPIs) could be collected in the simulated production scenario and in the experimental task with ID14:
- Fruit deliveries sent by the automated letter carrier at CPS1: 2
- Successful productions detected at CPS2: 0
- Production defects detected in the product: 1
- Completion of production compared to plan: no completion, late

To achieve this performance, the individual system analysis of the experimental task with ID14 shows the following neuron-induced activities:

- 2 fruit analyses performed, of which
  - fruit analyses performed for M1: 2
  - Fruit analyses performed for M2: 0
- 9 ”no-fruit” analyses performed, of which
  - ”No-fruit” analyses performed for M1: 2
  - ”No-fruit” analyses performed for M2: 7
- 9 pause instructions carried out, of which
  - pause instructions carried out for the short conveyor system: 2
  - pause instructions carried out on the long conveyor system: 7
- 2 transport instructions carried out, of which
  - transport instructions carried out on the short conveyor system: 2
  - Transport instructions carried out on the long conveyor system: 0

6 Evaluation

In order to satisfy design-science-oriented research approaches [16], it has been evaluated inhowfar knowledge transfers have been improved in the knowledge transfers scenarios demonstrated.

6.1 Experiment 1 - ID1

Since the production behavior shown here produces no waste and has no inefficiencies - all activities are required to successfully complete the production process - the **efficiency analysis** of the entire simulated production chain results in the following:

- 0 inefficient image analyses performed
- 0 inefficient breaks performed

As an **interpretation** of the neuron-instructed production behavior, the performance achieved and the individual system activities, the following can be concluded: There are no disruptions in the simulated production chain, as every neuronal output of CPS1 can be used efficiently by CPS2. There are no irrelevant pauses and image analyses.

As production in the scenario of the experimental task with ID1 runs efficiently and smoothly, corrective intervention by management is not necessary. There is therefore no need to derive **management interventions**, as the scenario is classified as ”on the beat” (see system status in Fig. 13 and Fig. 14). Optionally, the management could act proactively and (1) install a global scheduling mechanism that flexibly waits for the completion of each element of the production chain (the state of ID1 is thus guaranteed), or (2) the management could guarantee the ability of all ANNs to deal with the different variants of activation rate-activation cycle combinations of ID 1-14. In addition, (3) the outputs can be cached and a system-specific data provisioning mechanism can be installed that stores activation inputs and activation outputs in a time-dependent manner (thus guaranteeing that no values are accidentally overwritten) and injects corresponding time-relevant activations into the respective ANNs. The mechanism therefore provides the data provision logic as well as the rate and coupling management including a necessary time reset of recurrent ANNs.

In the **hypothesis conclusion**, it can be stated that the initial hypothesis H1 (”The synchronization of activation cycles with the same activation rates of distributed production sites promotes the trouble-free operation of production chains.”) can thus be confirmed on the basis of the analyses carried out here.

6.2 Experiment 2 - ID2

Since the production behavior shown here does not produce any rejects, but shows inefficiencies - an image analysis task and a pause task are not required to successfully complete the production process - the **efficiency analysis** of the entire simulated production chain results in the following:
- 1 inefficient image analysis performed
- 1 inefficient pauses performed

The **interpretation** of the neuron-instructed production behavior can be structured as follows: Disturbances occur because neuronal processing is realized with a temporal offset (delayed/early). However, every neuronal output of CPS1 can still be used by CPS2. However, the production chain is not efficient because there are unneeded pauses and irrelevant image analysis.

Because the production in the scenario of the experimental task with ID2 could not be realized efficiently and smoothly, a corrective intervention by the management is necessary. **Management interventions** can be derived from the following options: Since the scenario is classified as ”on the offbeat” (cf. system state in Fig. 13 and Fig. 14), management should bring the neural production chain into the beat by either (1) coupling the activation cycle of CPS2 with the cycle of CPS1, (2) coupling the activation cycle of CPS1 with the cycle of CPS1, or (3) setting up a global scheduling mechanism that waits for the completion of each element of the production chain (this would mean that the state of ID1 has been reached). Alternatively, the ANN (preferably from CPS2, but also from CPS1) can be retrained so that it can handle offbeats efficiently.

In the **hypothesis conclusion**, it can be stated that the initial hypothesis H2 (”Decoupled activation cycles with equal activation rates of distributed production sites lead to disruptions in production chains.”) can thus be confirmed on the basis of the analyses carried out here.

6.3 Experiment 3 - ID3

Since the production behavior shown here produces a reject and not a successful production product as well as various inefficiencies - not all activities are required to successfully carry out the production process - the **efficiency analysis** of the entire simulated production chain results in the following:
- 7 inefficiently performed image analyses
- 7 inefficient pauses performed

An **interpretation** of the neuron-instructed production behavior can be structured as follows: Disturbances occur in the production chain because the concatenated neural processing is not able to handle interval activations. Good results from CPS1 can therefore not be used by CPS2, as this is a new training task that is unknown to CPS2.

As production in the scenario of the experimental task with ID3 does not run efficiently and smoothly, corrective intervention by the management is necessary. The **management interventions** derived are as follows: Since the scenario is classified as ”on the interval-beat” (cf. system state in Fig. 13 and Fig. 14), management should eliminate irrelevant interval activations. This could be realized, for example, by (1) adjusting the activation rate of CPS2 so that it matches the cycle of CPS1, or by (2) installing a global planning mechanism that waits for the completion of each element of the production chain and thus realizes the state of ID1. Alternatively, additional sensors can be installed and corresponding ANNs can be retrained to handle intervals efficiently. Alternatively, (3) the outputs can be temporarily stored and a system-specific data provision mechanism can be installed that stores activation inputs and activation outputs in a time-dependent manner (and thus guarantees that no values are accidentally overwritten) and injects corresponding time-relevant activations into the respective ANNs. The mechanism therefore provides the data provision logic as well as the rate and coupling management including a necessary time reset of recurrent ANNs.

In the **hypothesis conclusion**, it can be stated that the initial hypothesis H3 ("Different activation rates in synchronized cycles of neural systems of distributed production sites lead to disruptions in production chains.") can thus be confirmed on the basis of the analyses carried out here.

6.4 Experiment 4 - ID9

Since the production behavior shown here produces a reject and not a successful production product as well as various inefficiencies - not all activities are required to successfully carry out the production process - the **efficiency analysis** of the entire simulated production chain results in the following:

- 7 inefficiently performed image analyses
- 7 inefficient pauses performed

The **interpretation** of the production behavior observed can be argued as follows: Disruptions occur in the neuron-based production chain because the concatenated neural processing is unable to handle (1) interval activations (intermittent activations) and (2) shifted (delayed/early) activations. The output correctly produced by CPS1 cannot be used by CPS2 because the training task is unknown to CPS2. Although the delay/timeliness shows the same behavior as in the experimental task with ID3, the activation behavior in the experimental task considered here is more complex and shows further possibilities for errors as well as further possibilities for inefficiencies due to the additional delay/timeliness.

As production in the scenario of the experimental task with the ID9 does not run efficiently and smoothly, corrective intervention by management is not necessary. The following **management interventions** are possible here, for example: Since the scenario is classified as "on the sifted interval-beat" (cf. system state in Fig. 13 and Fig. 14), management could first bring the neural production chain to the interval-beat so that the state "on the interval-beat" of the rhythmic state descriptions of dynamic systems is achieved. The management interventions of ID3 could then be applied. Alternatively, additional sensors could be installed and the artificial neural network of CPS2 could be retrained to efficiently handle (1) delays and (2) intervals. Alternatively, the output values can be temporarily stored and a system-specific data provision mechanism can be installed that stores activation inputs and activation outputs in a time-dependent manner (and thus guarantees that no values are accidentally overwritten) and injects corresponding time-relevant activations into the respective ANNs. The mechanism therefore provides the data provision logic as well as the rate and coupling management including a necessary time reset of recurrent ANNs.

In the **hypothesis conclusion**, it can be stated that the initial hypothesis H4 ("Different activation rates in asynchronized cycles - in the opposite sense of a standard of distributed production sites - prevent the operation of neuronally instructed production chains.") in the experimental task with the ID9 can thus be confirmed on the basis of the analyses carried out here.

6.5 Experiment 5 - ID14

Since the production behavior shown here produces a reject and not a successful production product as well as various inefficiencies - not all activities are required to successfully carry out the production process - the **efficiency analysis** of the entire simulated production chain results in the following:

- 5 inefficient image analyses performed
- 7 inefficient pauses performed

The **interpretation** of the neuron-instructed production behavior, the performance achieved and the individual system activities can be concluded as follows: Disruptions occur in the simulated production chain because neural processing in the neural fabric is unable to handle (1) interval activations, (2) multiple activations, and (3) postponed (delayed/early) activations. Neural outputs from CPS1 cannot be used because CPS1 self-destructs correctly initiated production activities due to unknown training tasks (tasks different from ID1). Even if a usable output from CPS1 is transferred to CPS2, it cannot be used here because CPS2 itself destroys correctly initiated production activities due to the unknown training task (compared to ID1). Irregularities in terms of (a) activation cycles, (b) activation rates in (c) all types of systems thus show the most complex analyses, the most non-transparent behavior and the most possibilities for errors as well as the most possibilities for inefficiencies.

Since production in the scenario of the experimental task with ID14 is inefficient and not running smoothly, corrective intervention by management is necessary. A derivation of **management interventions** could be realized as follows: Since the scenario is classified as "shifted no beat" (cf. system state in Fig. 13 and Fig. 14), management could first bring the neuronal production chain to the shifted interval-beat, so that the state "on the shifted interval-beat" of the rhythmic state descriptions of dynamic systems is achieved. The management interventions of ID9 can then be applied. Alternatively, additional sensors can be installed and the ANNs of CPS1 and CPS2 can be retrained to efficiently handle (1) interval and multiple activations, (2) irregular activation rates, (3) regularly delayed and premature activation shifts, and (4) irregular delays and premature activations. Alternatively, the output values can also be temporarily stored and a system-specific data provision mechanism can be installed that stores activation inputs and activation outputs on a time-dependent basis (and thus guarantees that no values are accidentally overwritten) and injects the corresponding time-relevant activations into the respective ANNs. The mechanism therefore provides the data provision logic as well as the rate and coupling management including a necessary time reset of recurrent ANNs.

As a **hypothesis conclusion**, it can be stated that the initial hypothesis H4 ("Different activation rates in asynchronized cycles - in the opposite sense of a standard of distributed production sites - prevent the operation of neuronally instructed production chains.") can also be confirmed in the experimental task with the ID14 based on the analyses carried out here.

7 Conclusion

In accordance with the DSRM [16], design-science oriented research demands for being communicated. Thus, the following concludes the paper by outlining insights achieved and justifying its contribution to the state-of-the-art.

Summary. This paper has presented a design and demonstration for cross-organization-wide, interacting ANN-based production system following different activation rates and activation cycles. These metaphorically are equivalent to multiple interwoven artificial brains being more or less in synchronization. It so extends the state-of-the-art of production system building and provides a new example for CPS, IoT and Digital Twins. The demonstration has clarified the usefulness of the prototype in the marmalade glass production scenario in multiple experiment settings examining different types of activation rate and cycle combinations. It so contributes with further examples of destructive and inefficient artificial knowledge transfers and novel coordination mechanisms for ANN-based decision support systems or rather distributed cognitive production networks. Further, the demonstration has confirmed that requirements of multi-site CPPS that are based on ANN instructions (or rather global, neuronally instructed production chains having multiple production facilities), that were specified in advance, have been satisfied, which is demanded by the design-oriented artifact creation [16].

Critical appraisal. The research question (*"How can different activation types of rate and cycle combinations in multi-site ANN be researched and improved?"*) can be answered with regard to the design of ANN-based production chains: individual production machines are setup as CPS, which is clarified by the prototype presented. They have a Digital Twin and they are based on the traditional tangible resource of production machines. Intelligence is carried out with the aid of AI requests communicated via MQTT based Internet channels and node-independent Docker containers providing AI expertise. This contributes with further examples for the domain of Production Management. These potential organization types are enabled because of the CPS capabilities, so that sensitive machines can adapt to the current context of a scenario and reflect on the machine's production tasks. By generating and providing different forms of AI instructions, specialized knowledge bases and data contexts are loaded so that artificial knowledge transfers are realized efficiently. This contributes to business process standards, since this leads to a novel form of process models and communication flows (see Fig. 11). Being embedded in the new simulated production chain infrastructure designed, the examination of ANN activation rates and cycles is enabled and new kinds of management interventions come into play. Thus, the knowledge base of Enterprise Architecture Management is extended. However, AI organization and collaboration standards are improved, because the harmonization of ANN activation and cycle opportunities can be controlled by techniques and management easily.

Limitations and Outlook. The results and insights presented here need to be limited in regard with the validation level. The technical functionality has been proven by a demonstrator, and the effects of different activation rates and cycles have been clarified by selected simulation scenarios. Validated knowledge transfer models have been applied for this. Future research will therefore examine the empirical examination of ANN-instructions and respective management interventions identified and stress the artifacts created by real-world conditions. This will be realized the aid of experiments offering the artifacts presented at this contribution. By measuring the time taken, feedback opportunities realized and the functioning of management interventions made by test persons of the three scenarios conceptualized here, a validation can be realized at a greater validation level.

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Appendices

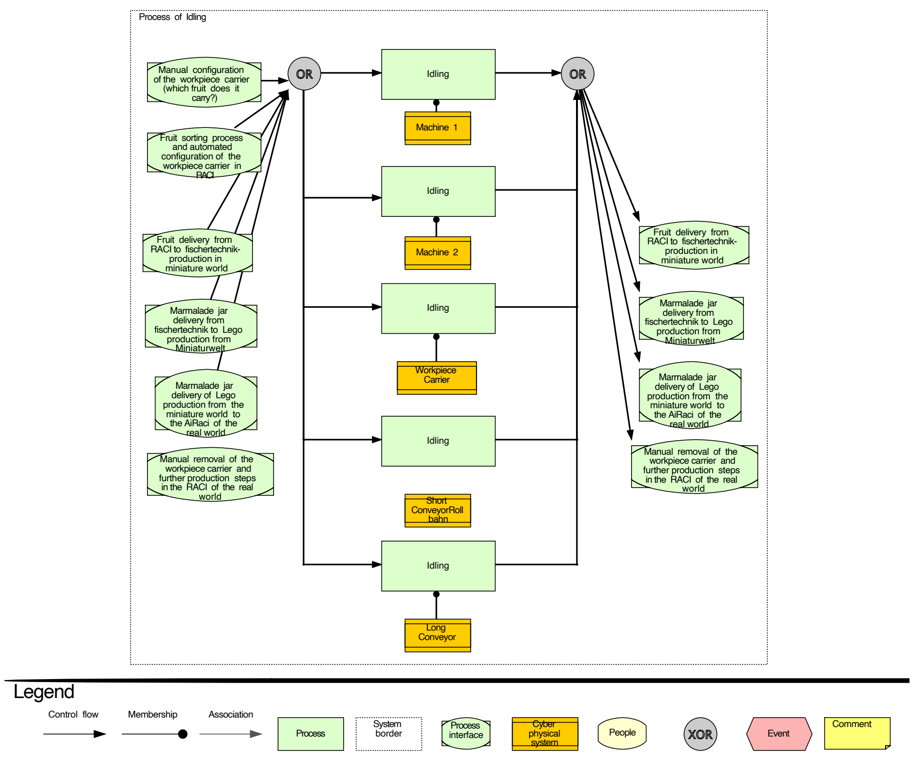


Fig. 12: The ProcessView of NMDL on the idling process of multi-site ANN.

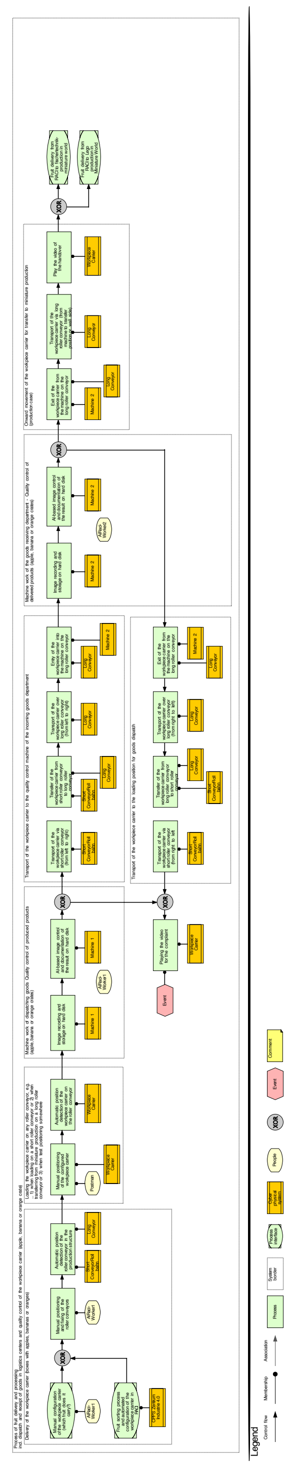
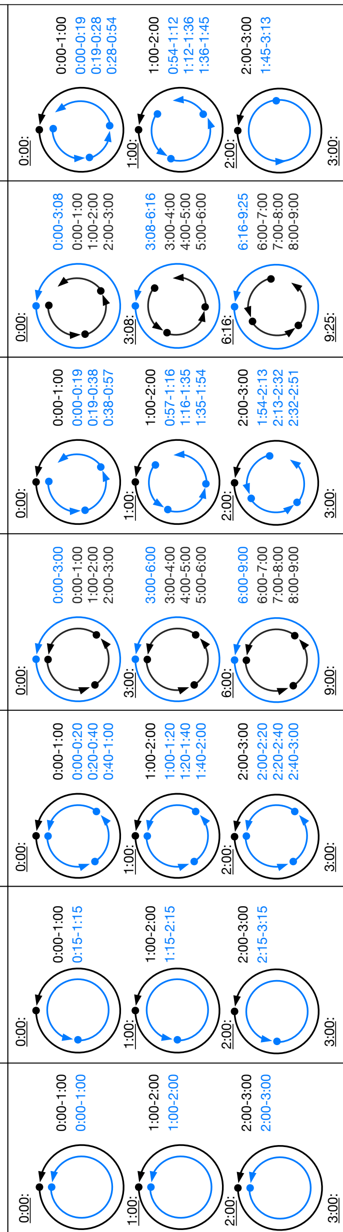


Fig. 13: The ProcessView of NMDL on the process of production tasks at the two AiRaci production sites.

ID	1	2	3	4	5	6	7
Hypothesis	H1	H2	$H3_a$	$H3_b$	$H3_c$	$H3_d$	$H3_e$
Cycles	coupled /synchronous	decoupled /asynchronous	coupled /synchronous	coupled /synchronous	coupled /synchronous	coupled /synchronous	coupled /synchronous
Rates	same	same	different (divisible)	different (duplicable)	different (indivisible)	different (unduplicable)	different (single irregular)
Parameters (examples)	Start CPS1 at 0:00 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = 1 cycle	Start CPS1 at 0:00 Start CPS2 at 0:15 Rate CPS1 = 1 cycle Rate CPS2 = 1 cycle	Start CPS1 at 0:00 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = 1/3 cycle	Start CPS1 at 0:00 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = 3 cycles	Start CPS1 at 0:00 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = 1/Pi cycles	Start CPS1 at 0:00 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = 1*Pi cycles	Start CPS1 at 0:00 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = variable
Visualization	0:00: 0:00-1:00 0:00-1:00 1:00: 1:00-2:00 1:00-2:00 2:00: 2:00-3:00 2:00-3:00 3:00:	0:00: 0:00-1:00 0:15-1:15 1:00: 1:00-2:00 1:15-2:15 2:00: 2:00-3:00 2:15-3:15 3:00:	0:00: 0:00-1:00 0:00-0:20 0:20-0:40 0:40-1:00 1:00: 1:00-2:00 1:00-1:20 1:20-1:40 1:40-2:00 2:00: 2:00-3:00 2:00-2:20 2:20-2:40 2:40-3:00 3:00:	0:00: 0:00-3:00 0:00-1:00 1:00-2:00 2:00-3:00 3:00: 3:00-6:00 3:00-4:00 4:00-5:00 5:00-6:00 6:00: 6:00-9:00 6:00-7:00 7:00-8:00 8:00-9:00 9:00:	0:00: 0:00-1:00 0:00-0:19 0:19-0:38 0:38-0:57 1:00: 1:00-2:00 0:57-1:16 1:16-1:35 1:35-1:54 2:00: 2:00-3:00 1:54-2:13 2:13-2:32 2:32-2:51 3:00:	0:00: 0:00-3:08 0:00-1:00 1:00-2:00 2:00-3:00 3:08: 3:08-6:16 3:00-4:00 4:00-5:00 5:00-6:00 6:16: 6:16-9:25 6:00-7:00 7:00-8:00 8:00-9:00 9:25:	0:00: 0:00-1:00 0:00-0:19 0:19-0:28 0:28-0:54 1:00: 1:00-2:00 0:54-1:12 1:12-1:36 1:36-1:45 2:00: 2:00-3:00 1:45-3:13 3:00:
System state (rhytmic interpretation)	periodically (on the beat)	periodically (on the offbeat)	periodically (on the interval-beat)	periodically (on the manifold-beat)	periodically (off the interval-beat)	periodically (off the manifold-beat)	chaotic (off the beat)



Legend:
- Start of AI usage of *Machine1*
- Start of AI usage of *Machine2*
- End of AI usage of *Machine1*
- End of AI usage of *Machine2*
- Period of AI Usage of *Machine1*
- Period of AI Usage of *Machine1*

abc - Time state of global system clock

Fig. 14: The DoE on activation rates and activation cycles of multi-site ANN (part I).

ID	8	9	10	11	12	13	14
Hypothesis	$H3_f$	$H4_a$	$H4_b$	$H4_c$	$H4_d$	$H4_e$	$H4_f$
Cycles	coupled /synchronous	decoupled /asynchronous	decoupled /asynchronous	decoupled /asynchronous	decoupled /asynchronous	decoupled /asynchronous	decoupled /asynchronous
Rates	different (double irregular)	different (divisible)	different (duplicable)	different (indivisible)	different (unduplicable)	different (single irregular)	different (double irregular)
Parameters (examples)	Start CPS1 at 0:00 Start CPS2 at 0:00 Rate CPS1 = variable Rate CPS2 = variable	Start CPS1 at 0:00 Start CPS2 at 0:15 Rate CPS1 = 1 cycle Rate CPS2 = 1/3 cycle	Start CPS1 at 0:15 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = 3 cycles	Start CPS1 at 0:00 Start CPS2 at 0:02 Rate CPS1 = 1 cycle Rate CPS2 = 1/Pi cycles	Start CPS1 at 0:02 Start CPS2 at 0:00 Rate CPS1 = 1 cycle Rate CPS2 = 1*Pi cycles	Start CPS1 at 0:00 Start CPS2 at 0:02 Rate CPS1 = 1 cycle Rate CPS2 = variable	Start CPS1 at 0:00 Start CPS2 at 0:02 Rate CPS1 = variable Rate CPS2 = variable
Visualization (examples)	0:00: 0:00-0:48 0:00-0:19 0:19-0:28 0:28-0:54 1:00: 0:48-1:46 0:54-1:12 1:12-1:36 1:36-1:42 2:00: 1:46-2:36 1:42-3:15 3:00:	0:00: 0:00-1:00 0:15-0:35 0:35-0:55 0:55-1:15 1:00: 1:00-2:00 1:15-1:35 1:35-1:55 1:55-2:15 2:00: 2:00-3:00 2:15-2:35 2:35-2:55 2:55-3:15 3:00:	0:00: 0:00-3:00 0:15-1:15 1:15-2:15 2:15-3:15 3:00: 3:00-6:00 3:15-4:15 4:15-5:15 5:15-6:15 6:00: 6:00-9:00 6:15-7:15 7:15-8:15 8:15-9:15 9:00:	0:00: 0:00-1:00 0:02-0:21 0:21-0:40 0:40-0:59 1:00: 1:00-2:00 0:59-1:18 1:18-1:37 1:37-1:56 2:00: 2:00-3:00 1:56-2:15 2:15-2:34 2:34-2:53 3:00:	0:00: 0:00-3:08 0:02-1:02 1:02-2:02 2:02-3:02 3:08: 3:08-6:16 3:02-4:02 4:02-5:02 5:02-6:02 6:16: 6:16-9:25 6:02-7:02 7:02-8:02 8:02-9:02 9:25:	0:00: 0:00-1:00 0:02-0:21 0:21-0:30 0:30-0:56 1:00: 1:00-2:00 0:56-1:14 1:14-1:38 1:38-1:47 2:00: 2:00-3:00 1:47-3:15 3:00:	0:00: 0:00-0:48 0:02-0:21 0:21-0:30 0:30-0:56 1:00: 0:48-1:46 0:56-1:14 1:14-1:38 1:38-1:47 2:00: 1:46-2:36 1:47-3:15 3:00:
System state (rhytmic interpretation)	chaotic (no beat)	periodically (on shifted interval-beat)	periodically (on shifted manifold-beat)	periodically (off shifted inverval-beat)	periodically (off shifted manifold-beat)	chaotic (off the shifted beat)	chaotic (shifted no beat)

Legend:
- Start of AI usage of *Machine1*
- Start of AI usage of *Machine2*
- End of AI usage of *Machine1*
- End of AI usage of *Machine2*
- Period of AI Usage of *Machine1*
- Period of AI Usage of *Machine1*
- abc - Time state of global system clock

Fig. 15: The DoE on activation rates and activation cycles of multi-site ANN (part II).