

# Stability Analysis Scheme for Autonomously Controlled Production Networks with Transportations

Sergey Dashkovskiy, Michael Görges and Lars Naujok

**Abstract** In this paper, we present a scheme for the stability analysis of autonomously controlled production networks with transportations. We model production networks by differential equations and discrete event simulation models (DES) from a mathematical and engineering point of view, where transportation times are considered in the models as time delays. Lyapunov functions as a tool to check the stability of networks are used to calculate stability regions. Then, this region is refined using the detailed DES. This approach provides a scheme to determine stability regions of networks with less time consumption in contrast to a pure simulation approach. In presence of time delays, new challenges in the analysis occur, which is pointed out in this paper.

## Introduction

Production networks are used to describe company or cross-company owned networks with geographically dispersed plants (Wiendahl and Lutz 2002), which are connected by transport routes. One of the approaches to handle such complex systems is to shift from centralized to decentralized or autonomous control.

---

S. Dashkovskiy (✉)

Department of Civil Engineering, University of Applied Sciences Erfurt, Erfurt, Germany  
e-mail: sergey.dashkovskiy@fh-erfurt.de

M. Görges

BIBA-Bremer Institut für Produktion und Logistik GmbH at the University of Bremen,  
Bremen, Germany  
e-mail: goe@biba.uni-bremen.de

L. Naujok

Centre for Industrial Mathematics, University of Bremen, Bremen, Germany  
e-mail: larsnaujok@math.uni-bremen.de

In this paper, we consider a certain autonomously controlled production network scenario consisting of six interconnected plants focus. In the context of production networks, the concept of autonomous control enables intelligent logistic objects such as parts and orders, for example, to decide about routes through the system autonomously. The concept of autonomous control aims at affecting the systems performance positively (Windt and Hülsmann 2007).

Different autonomous control methods have been developed in the literature (Scholz-Reiter et al. 2011b). In this paper, the local rational autonomous control method queue length estimator (QLE) is considered for autonomous decision making on the network level and on the shop-floor level. On the shop-floor level, the QLE enables parts to choose a workstation according to local information about their current workload. In contrast, parts using this method on the network level estimate the waiting times at succeeding production plants. According to this method, they will choose the next possible production plant with the shortest estimated waiting time.

Stability of a production network means that the work in progress (WIP) remains bounded over time. Instability, by means of an unbounded growth of the WIP, may cause high inventory costs, downtimes of machines or loss of customers, for example. The implementation of autonomous control methods can lead to instability of the system (Windt 2006; Philipp et al. 2007). Hence, it is necessary for logistic systems to derive parameters, which guarantee stability.

For the stability analysis, we provide a dual approach: a mathematical and an engineering point of view. Based on retarded functional differential equations, Lyapunov-Razumikhin functions (Teel 1998) are used to calculate a stability region, which includes parameters for which the network is stable (Dashkovskiy and Naujok 2010c; Dashkovskiy et al. 2010a). These stability parameters are implemented into a more detailed microscopic model, where all plants are represented by a complete shop floor. This microscopic view, models the scenario with the help of a discrete event simulation (DES) tool. Using this approach, the calculated stability region will be refined. The advantage is that we first apply the mathematical theory to find in a very fast way those parameters, where stability is guaranteed. A refinement is performed by simulations, in order to enlarge the set of parameters, which guarantee stability. This scheme provides an identification of a stability region with less time consumption in contrast to a pure simulation approach, where the time needed for the simulations increases exponentially by increasing the number of plants, parts and machines.

An existing work on stability analysis for production networks without transportations can be found in Scholz-Reiter et al. (2011a), where the mentioned scheme was firstly introduced. Here, we adopt this approach to networks with transportations using Lyapunov tools for networks presented in Dashkovskiy and Naujok (2010c) and applied in Dashkovskiy et al. (2010a, 2011a). In presence of transportations, i.e., time delays, the dynamics of the network is much more complex than the dynamics without transportations. The worst-case approach of the mathematical analysis this leads to a rough calculation of the stability region that is then calculated more precisely with help of DES. The identification of stable

or unstable behavior of the network using the DES for the refinement of the stability region is a challenging task and the abort criterion used in Scholz-Reiter et al. (2011a) needs to be adapted for networks with time delays.

### Modeling

For the illustration of the novel stability analysis approach a particular production network has been chosen, which is described in this section.

The production network in Fig. 1 consists of six geographically distributed production locations, which are connected by transportation routes. In this paper we consider the material flow between the locations, described in Fig. 1 by arrows. In this scenario the  $x_i(t) \in R$  for  $i = 1, \dots, 6$  represents the WIP of the  $i$ th location at time  $t$ , where  $t \in R_+$  and  $R_+$  denotes all positive real values. In the rest of this paper for the  $i$ th production location we write *subsystem i*. The network of all six subsystems we name simply whole system.

Each plant of the network is represented by a complete shop floor scenario. It consists of three parallel production lines. Every line has three workstations and an input buffer in front of each workstation. The structure allows the parts to switch lines at every stage. The decision about changing the line is made by the part itself by internal control rules. This rule on the shop floor level is the QLE.

Subsystem 1 gets some raw material from an external source, denoted by  $u(t) \in R$  and some material from subsystem 6. The material will be processed with a certain production rate  $\tilde{f}_1$ . Then, a truck loads the processed parts and transports them to the subsystem 2 or 3, according to the QLE. The transportation time from subsystem  $i$  to  $j$  is denoted by  $\tau_{ij}$ . The parts will be processed with the rate  $\tilde{f}_2$  or  $\tilde{f}_3$  and sent to subsystem 4 or 5, according to the QLE. After processing the parts with the rates  $\tilde{f}_4$  and  $\tilde{f}_5$  they will be sent to subsystem 6 and processed there  $\tilde{f}_6$  with the rate  $\tilde{f}_6$ . Then, 90 % of the production will be delivered to some customers outside of the network and 10 % of the production of subsystem 6 will be sent back to subsystem 1. This can be interpreted as recycling of the waste produced in subsystem 6, for example.

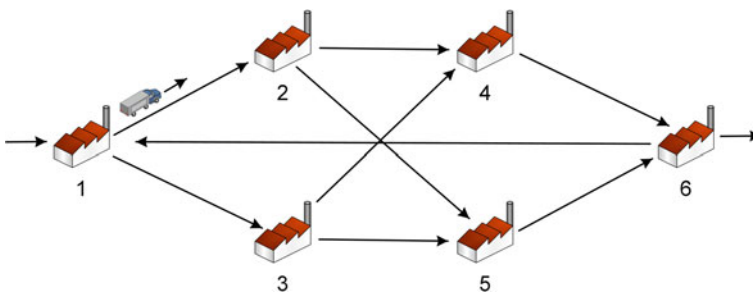


Fig. 1 The particular production network

There are two levels of aggregation and modeling. The macroscopic view focuses on the network level, which consists of production plants only. On the microscopic level, the network is represented more detailed. In addition to the macroscopic view, the microscopic view represents the plants as a set of interconnected machines. In the following these two views will be described.

### Aggregated View Using ODEs

In the macroscopic approach we provide our description and analysis from a mathematical point of view. The internal structure on the shop floor level of all subsystems is ignored. All subsystems are autonomously controlled by means of an autonomous adjustment of the production rates. As in Scholz-Reiter et al. (2011a), the production rate for the subsystem  $i$  can be modeled by

$$\tilde{f}_i(x_i(t)) := \alpha_i(1 - \exp(-x_i(t))), i = 1, \dots, 6,$$

where  $\alpha_i \in R_+$  is the (constant) maximal production rate of the subsystem  $i$ . Note that one can choose any other rate, which fits to a certain scenario.  $\tilde{f}_i$  converges to  $\alpha_i$ , if the WIP of the subsystem  $i$  is large and  $\tilde{f}_i$  tends to zero, if the WIP of the subsystem  $i$  tends to zero. Accordingly, a huge influx of raw material causes an increase of the production rate close to the maximum, whereas less influx of raw material leads to a production rate, which is almost zero.

When modeling the system by retarded differential equations, we assume that the processed material will be transported at time  $t$  to a subsystem according to the QLE and arrives at the succeeding subsystem at the time  $t + \tau_{ij}$ , where  $\tau_{ij}$  can be interpreted as transportation time needed for the transportation from subsystem  $i$  to  $j$ . Here, no delay within the production process is implemented. Note that one can use variable transportation times  $\tau_{ij}$  instead of constant ones such as state- or time-dependent variables. For example, disturbances on the transport routes can be taken into account choosing variable  $\tau_{ij}$ .

A retarded differential equation describes the rate of change of the WIP along the time. We model the network by retarded differential equations as follows:

$$\begin{aligned} \dot{x}_1(t) &:= u(t) + \frac{1}{10}\tilde{f}_6(x_6(t - \tau_{61})) - \tilde{f}_1(x_1(t)), \\ \dot{x}_2(t) &:= \tilde{c}_{12}\tilde{f}_1(x_1(t - \tau_{12})) - \tilde{f}_2(x_2(t)), \\ \dot{x}_3(t) &:= \tilde{c}_{13}\tilde{f}_1(x_1(t - \tau_{13})) - \tilde{f}_3(x_3(t)), \\ \dot{x}_4(t) &:= \tilde{c}_{24}\tilde{f}_2(x_2(t - \tau_{24})) + \tilde{c}_{34}\tilde{f}_3(x_3(t - \tau_{34})) - \tilde{f}_4(x_4(t)), \\ \dot{x}_5(t) &:= \tilde{c}_{25}\tilde{f}_2(x_2(t - \tau_{25})) + \tilde{c}_{35}\tilde{f}_3(x_3(t - \tau_{35})) - \tilde{f}_5(x_5(t)), \\ \dot{x}_6(t) &:= \tilde{f}_4(x_4(t - \tau_{46})) + \tilde{f}_5(x_5(t - \tau_{56})) - \tilde{f}_6(x_6(t)), \end{aligned} \tag{1}$$

where  $\tilde{c}_{ij}$  represent the QLE. The external input is chosen according to fluctuations as  $u(t) := AV(\sin(t) + 1) + 5$ , where  $AV \in R_+$ .

$x_i(t)$  may also represent other relevant parameters of the system, e.g., the number of unsatisfied orders. One can extend or change the given production network to describe any other scenario that can be more large and complex. It is possible to perform a stability analysis for the extended system.

### ***Detailed View Using DES***

By using a DES approach, a more detailed modeling is performed. Due to the lower aggregation level and the discrete nature of this modeling approach some parameters from the aggregated differential equation based model have to be adjusted. The DES represents the flows of materials by discrete parts passing through the network. This requires an adjustment of the input rate in plant 1. In the DES model the arrival rate  $u(t)$  is cumulated. Whenever this cumulated arrival rate reaches an integer value a part enters the system at the corresponding time point  $t$ . A second adjustment concerns the production rates of all production plants. In the detailed view the plants represent a shop-floor scenario with  $3 \times 3$  machines. Due to the parallel machines offered by the shop-floor, the production rate of a plant has to be distributed to these parallel machines. In the case at hand each work station  $j$  in the plant  $i$  has a maximal production rate of  $\alpha_{ij} = \frac{\alpha_i}{3}$ .

### **Stability Analysis**

In this section, the scheme and the used tools of a stability analysis are described.

We consider nonlinear dynamical systems of the form

$$\dot{x}(t) = f(x^t, u(t)), \quad (2)$$

which are called retarded functional differential equations (RFDE), where  $x^t \in C([- \Delta, 0], R^N)$  is defined by  $x^t(\tau) := x(t + \tau)$ ,  $\tau \in [- \Delta, 0]$ .  $\Delta$  denotes the maximal involved delay and  $C([- \Delta, 0], R^N)$  denotes the Banach space of continuous functions defined on  $[- \Delta, 0]$  equipped with the norm  $\|x\|_{[- \Delta, 0]} := \max_i \max_{t \in [- \Delta, 0]} |x_i(t)|$ . We denote the Euclidian norm in  $R^n$  by  $|\cdot|$  and the essential supremum norm for essentially bounded functions  $u$  in  $R_+$  by  $\|u\|_\infty$ .  $u \in R^M$  is the external input of the system, which is an essentially bounded measurable function and  $f : C([- \Delta, 0], R^N) \times R^M \rightarrow R^N$  is a nonlinear and locally Lipschitz continuous functional to guarantee that the system (1) has a unique solution  $x(t)$  for every initial condition  $x_0 = \xi$  for any  $\xi \in C([- \Delta, 0], R^N)$ . An interconnected system is described by RFDEs of the form

$$\dot{x}_i(t) = f_i(x_1^t, \dots, x_n^t, u_i(t)), \tag{3}$$

$i = 1, \dots, n$ , where  $x_i^t \in C([-Δ, 0], \mathbb{R}^{N_i})$ ,  $u_i \in \mathbb{R}^{M_i}$  and  $f_i : C([-Δ, 0], \mathbb{R}^N) \times \mathbb{R}^{M_i} \rightarrow \mathbb{R}^{N_i}$ . Defining  $N := \sum_{i=1}^n N_i$ ,  $m := \sum_{i=1}^n M_i$ ,  $x = (x_1^T, \dots, x_n^T)^T$ ,  $u := (u_1^T, \dots, u_n^T)^T$  and  $f := (f_1^T, \dots, f_n^T)^T$ , (3) can be written in the form (2).

We define local input-to-state stability (LISS) for each subsystem of (3). For system (2), the definition of LISS can be found in Dashkovskiy et al. (2010a). The used classes of functions can also be found in Dashkovskiy et al. (2010a).

**Definition 1** The  $i$ th subsystem of (3) is called LISS, if there exist constants  $\rho_i, \rho_j^i, \rho_i^u > 0, \gamma_{ij}, \gamma_i \in K_\infty$  and  $\beta_i \in KL$ , such that for all initial functions  $\|x_i\|_{[-Δ, 0]} \leq \rho_i, \|x_j\|_{[-Δ, \infty)} \leq \rho_j^i, j \neq i$  and all inputs  $\|u_i\|_\infty \leq \rho_i^u$  it holds

$$\|x_i(t)\| \leq \max \left\{ \beta_i \left( \|\xi_i\|_{[-Δ, 0]}, t \right), \max_{j \neq i} \gamma_{ij} \left( \|x_j\|_{[-Δ, \infty)} \right), \gamma_i \left( \|u_i\|_\infty \right) \right\} \tag{4}$$

$\forall t \in \mathbb{R}_+, \gamma_{ij}$  and  $\gamma_i$  are called (nonlinear) gains. Note that, if  $\rho_i, \rho_j^i, \rho_i^u = \infty$  then the  $i$ th subsystem is ISS.

LISS and ISS, respectively, mean that the norm of the trajectories of each subsystem is bounded. Furthermore, we define the *gain matrix*  $\Gamma := (\gamma_{ij}), i, j = 1, \dots, n, \gamma_{ii} = 0$ , which defines a map  $\Gamma : \mathbb{R}_+^n \rightarrow \mathbb{R}_+^n$  by

$$\Gamma(s) := \left( \max_j \gamma_{1j}(s_j), \dots, \max_j \gamma_{nj}(s_j) \right)^T, s \in \mathbb{R}_+^n. \tag{5}$$

To check, if the whole network has the ISS property a small gain condition is needed, which is of the form

$$\Gamma(s) \not\geq s, \forall s \in \mathbb{R}_+^n \setminus \{0\}. \tag{6}$$

Notation  $\not\geq$  means that there is at least one component  $i \in \{1, \dots, n\}$  such that  $\Gamma(s)_i < s_i$ . A local version of the small gain condition (LSGC) can be found in Dashkovskiy and Ruffer (2010b). A useful tool to verify LISS for time-delay systems are Lyapunov-Razumikhin functions (LRF) or Lyapunov–Krasovskii functionals (LKF), see Teel (1998) and Dashkovskiy and Naujok (2010c). In this paper, we use LRF, but the analysis considering LKF is similar. For systems of the form (2) one can find the definition of LRF for example in Teel (1998) and for systems of the form (3) LRFs are defined in Dashkovskiy and Naujok (2010c). With these definitions we quote the following:

**Theorem 1** Consider the interconnected system (3). Assume that each subsystem has an LISS-LRF  $V_i, i = 1, \dots, n$ . If the corresponding gain-matrix  $\Gamma$  satisfies the LSGC, then the whole system of the form (2) is LISS.

The proof can be found in Dashkovskiy and Naujok (2010c) with corresponding changes according to the LISS property. This Theorem completes the mathematical part of the stability analysis and the identification of the stability region of the network, which is the set of parameter constellations guaranteeing LISS: One has to find a LISS-LRF for each subsystem of (3) and to check, if the LSGC is satisfied. From these conditions the stability region will be identified in a first step. From Theorem 1 we know that the whole network possesses the LISS property.

In a second step the identified stability region will be refined using DES. By LRFs and the LSGC, we obtain a rough estimation of the stability region. The DES can investigate the system and its behavior in a more detailed way. The drawback of the identification of the stability region based only of the DES approach is that one has to simulate all possible combinations of free systems variables. By a linear growth of the number of subsystems and the variables this leads to an exponential growth of time needed for the simulation runs such that a determination of the stability region in an acceptable time is not possible.

The advantage of the presented approach in this paper is that the identification of the stability region using the mathematical approach is possible in a short time, where only few parameter constellations are left for investigation in view of stability. This can be performed by the DES and the stability region of networks can be identified with less time consumption in total in contrast to an approach only based on simulation runs. An illustration of the scheme can be found in Scholz-Reiter et al. (2011a).

## Stability Evaluation

In this section, we determine the stability region of the scenario, introduced in section [Modeling](#) from a mathematical point of view and refine it using the DES.

### *Determining Stability Regions*

We choose  $V_i(x_i) = x_i, i = 1, \dots, 6$  as the LRF candidates for the subsystems, define the Lyapunov gains for the first subsystem by

$$\chi_u(u(t)) := -\ln\left(1 - \frac{u(t)(\|u\|_\infty + 0.1 \cdot \alpha_6)}{\|u\|_\infty(1 - \varepsilon_u)\alpha_1}\right), 1 > \varepsilon_u > 0,$$

$$\chi_{61}(\|V_6^d(x_6)\|) := -\ln\left(1 - \frac{\|u\|_\infty + 0.1 \cdot \alpha_6}{(1 - \varepsilon_{61})\alpha_1}(1 - \exp(-\|V_6^d(x_6)\|))\right), 1 > \varepsilon_{61} > 0.$$

where  $\|V_i^d(x_i(t))\| := \max_{s \in [t-\Delta, t]} |V(x(s))|$ . The gains of the other subsystems are chosen accordingly and by similar calculations as in (Dashkovskiy and Naujok 2010c), we can show that  $V_i(x_i)$  are the LRFs of the subsystems. All subsystems

are LISS and the gain-matrix consisting of  $\chi_{ij}$  satisfies the small-gain condition. All the calculations are skipped, because of the limited space.

To guarantee that the Lyapunov gains are well-defined, we get conditions for  $\alpha_i$ :  $\alpha_1 > \|u\|_\infty + 0.1\alpha_6$ ;  $\alpha_2 > \alpha_1$ ;  $\alpha_3 > \alpha_1$ ;  $\alpha_4 > \alpha_2 + \alpha_3$ ;  $\alpha_5 > \alpha_2 + \alpha_3$ ;  $\alpha_6 > \alpha_5 + \alpha_4$  from which we get that subsystem 1 is LISS with  $\rho_1^u := \alpha_1 - \alpha_6 > \|u\|_\infty$ . Note that these conditions are derived only for the particular scenario. For other scenarios, one may get other stability conditions. Subsystems 2–5 are ISS. If these conditions are satisfied for any input  $u(t)$ , we get by Theorem 1 that the whole system is LISS, i.e., the WIP of the whole system is bounded. Note that the choice of the input  $u(t)$  can be arbitrary. The higher  $\|u\|_\infty$  is, the higher the maximal production rates are needed to guarantee the fulfillment of the conditions for  $\alpha_i$  and to guarantee stability.

### ***Refining Stability Regions by Using a DES Model***

The abort criterion defines unstable states of the network as follows: a simulation run is considered to be unstable whenever the WIP starts to grow persistently in a predefined time interval about 10 % (Scholz-Reiter et al. 2011a). On the basis of this abort criterion, an approach is proposed which reduces the maximal production rate of all plants in different simulation runs in steps of 1 % until the abort criterion is satisfied. The reduced maximal production rates are the results of the refinement. Due to the autonomous decision making on the network level the quantities shipped between the locations may vary. A static approach, which reduces the production rates of all plants uniformly seem not to be suitable. Thus, the approach used in this paper extends the static approach presented above. The new refinement procedure has to take into account that the shipment between plants is related to the production rates of preceding plants. Thus, the refinement procedure varies the maximal production rate of each plant separately.

In order to provide a systematic refinement of the production rates, an approach based on an algorithmic scheme is proposed: The refinement algorithm aims at finding the smallest maximal production rates for all plants guaranteeing stability. In the beginning the algorithm and its parameters are initialized. It starts with an arbitrarily network configuration, which is considered to be stable. The algorithm consists of two iterative loops. The inner iteration reduces stepwise the maximal production rates of the plants at one network stage  $S$  and starts the simulation. This iteration will be repeated until the abort criterion is satisfied. After this, the counter  $S$  is set to the next network stage and the inner loop will be repeated again, until the counter  $S$  equals the number of the last production stage. In this case the counter of the second iteration  $i$  is increased and the counter  $S$  is set again to the first network stage. The second outer iteration causes the repetition of the inner iteration until a pre-defined amount of iteration steps are reached.



### Results of the Stability Analysis

We set  $\tau_{ij} = 1$ . The results of the analysis, i.e., the identification of stability regions, are the same for other values of  $\tau_{ij}$ . Figure 2 shows the results of the mathematical stability analysis for the production plant 1 against the arrival rate amplitude variation AV. The figures for the other plants are similar. Within the mathematically identified stability region, stability of the network can be guaranteed. However, below the border of this region stable systems behavior neither can be guaranteed nor negated. In this area, the stability of the network is investigated by simulations. For the refinement of the stability region the algorithm described above is applied, where the calculated bounds of the stability region are the initial values. The simulated stability region of Fig. 2 is the result of the refinement. The simulation model has stable behavior above the simulative derived stability border. Below this border, unstable behavior was observed.

Comparing the results of the mathematically determined and the refined stability regions, it can be noticed that gap between the mathematical and the simulated results grows with increasing AV. For  $AV = 60$ , the difference between the simulated and the calculated bounds of stability is 67 %. This can be explained by the usage of the worst case within the mathematical stability property ISS, namely the supremum norm. In particular, for oscillating inputs, like in the case at hand the maximal value is used to derive stability parameters. By increasing AV this leads to bigger mathematical bounds of stability. Figure 3 illustrates the results of the simulation based refinement more detailed. It depicts the WIP against time of all plants for a simulation run with  $AV = 4$ . The left column of Fig. 3 shows the results for the stable situation ( $\alpha_1 = 10.4, \alpha_2 = 5.41, \alpha_3 = 5.41, \alpha_4 = 5.2$ ,

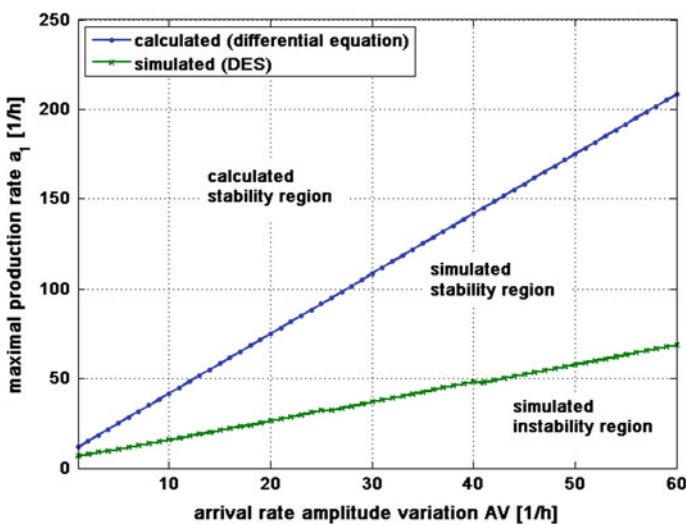


Fig. 2 Stability region of plant 1 for increasing AV

$\alpha_5 = 5.2, \alpha_6 = 12.13$ ). By contrast the right column shows the results of an unstable situation ( $\alpha_2 = 4.98$  and  $\alpha_3 = 4.98$ ). The results of the right column are determined by reducing the maximal production rates of network stage by 1 %.

In the unstable situation, the maximal production rate of plant 2 and plant 3 is not sufficient to process the incoming material. The WIP of this plant starts to grow consequently and the network is considered to be unstable. This example shows that the mathematically determined stability region can be refined to a sharp and precise bound of stability. Note that the oscillating behavior is caused by the presence of time delays.

Summarizing these results it shows the symbiotic character of the dual approach combining mathematical stability analysis and simulation. The simulation of the model leads to sharp and accurate stability borders. However, without a properly chosen start configuration a time intensive trial and error approach is necessary. Here the mathematical theory helps to find parameter constellations which guarantee the stability of the network. These results are used as start parameters in the simulation model. This reduces the range of possible parameters to test in the simulation approach. Accordingly, the presented stability analysis scheme can be performed more efficient compared to a trial and error approach.

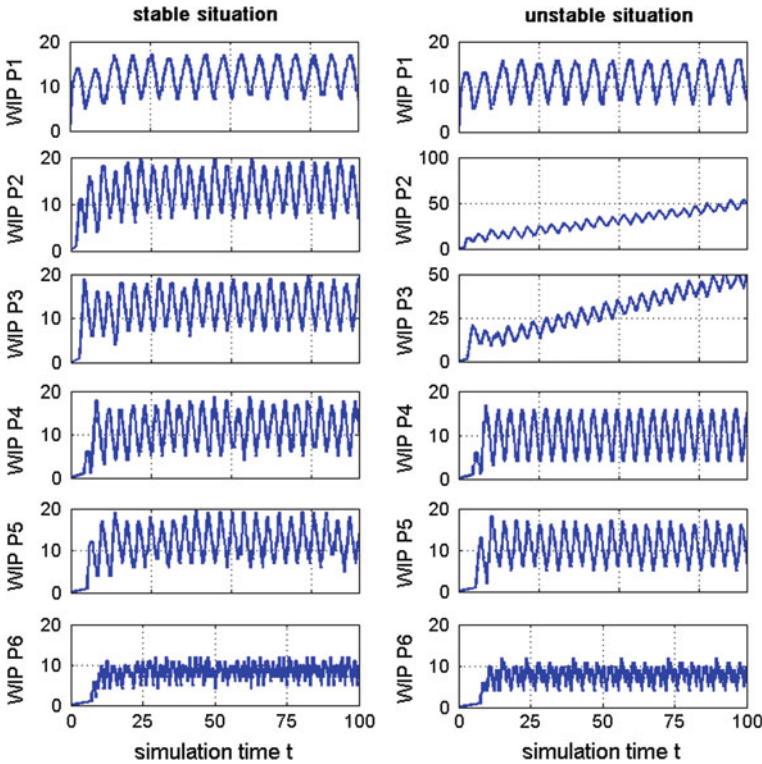


Fig. 3 Stable and unstable situation for  $AV = 4$

## Summary and Outlook

This paper presented an approach for the stability analysis of autonomously controlled production networks with transportations. Tools from mathematical stability theory were combined with the simulation of dynamic systems, which has the advantage of less time consumption in contrast to a pure simulation approach to identify stability regions. The approach has been applied to an exemplarily autonomously controlled production network in order to identify parameter constellation which guarantee the stability of the entire network.

Future research will focus on applying this combined approach to more complex scenarios with different autonomous control methods. The presented approach can be used for the identification of regions of effective or optimal behavior of the network in view of economic or logistic goals.

**Acknowledgments** This research was supported by the German Research Foundation (DFG) as part of the Collaborative Research Centre 637 “Autonomous Cooperating Logistics Processes—A Paradigm Shift and its Limitations”.

## References

- Dashkovskiy S, Karimi HR, Kosmykov M, Mironchenko A, Naujok L (2010a) Application of the LISS Lyapunov-Krasovskii small-gain theorem to autonomously controlled production networks with time-delays. In: Proceedings of SysTol, Nice, France, pp 765–770, 06 Oct 2008
- Dashkovskiy SN, Rüffer BS (2010b) Local ISS of large-scale interconnections and estimates for stability regions. *Syst Control Lett* 59(3–4):241–247
- Dashkovskiy S, Naujok L (2010c) Lyapunov-Razumikhin and Lyapunov-Krasovskii theorems for interconnected ISS time-delay systems. In: Proceedings of the 19th MTNS 2010, Budapest, Hungary, pp 1179–11845–9 July
- Dashkovskiy S, Görge M, Kosmykov M, Mironchenko A, Naujok L (2011) Modeling and stability analysis of autonomously controlled production networks. *Logistics Res* 3(2):145–157
- Philipp T, de Beer C, Windt K, Scholz-Reiter B (2007) Evaluation of autonomous logistic processes—analysis of the influence of structural complexity. In: Hülsmann W (ed) Understanding autonomous cooperation and control, Springer, Berlin, pp 303–324
- Scholz-Reiter B, Dashkovskiy S, Görge M, Naujok L (2011a) Stability analysis of autonomously controlled production networks. *Int J Prod Res* 49(16):4857–4877
- Scholz-Reiter B, Görge M, Jagalski T (2011b) Modeling and analyzing integrated autonomously controlled production and transport processes. In: Proceedings of the 21st international conference on production research. ICPR 21, CD-Rom, p 6
- Teel AR (1998) Connections between Razumikhin-type theorems and the ISS nonlinear small gain theorem. *IEEE Trans Automat Control* 43(7):960–964
- Wiendahl HP, Lutz S (2002) Production in networks. *Ann CIRP Manuf Technol* 51(2):1–14
- Windt K, Hülsmann M (2007) Changing paradigms in logistics—understanding the shift from conventional control to autonomous cooperation and control. In: Hülsmann W (eds) Understanding autonomous cooperation and control, Springer, Berlin, p 4–16
- Windt K (2006) Selbststeuerung intelligenter Objekte in der Logistik. In: Vec M, Hütt M, Freund A (eds) Selbstorganisation—Ein Denksystem für Natur und Gesellschaft, Böhlau, Köln, pp 271–314