Logistics Networks: Coping with Nonlinearity and Complexity

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1 Introduction

Nowadays the complexity of logistics is a buzzword spreading in business, media and everyday practice. However, the study of logistics networks from the point of view of complex dynamical systems theory has started only recently. In the past decade, physicists have been more and more interested in interdisciplinary fields such as biophysics, traffic physics, econophysics, or sociophysics [28, 7, 13]. Also, the study of production processes and logistics networks has become attractive [27, 37, 1], although the title of the book "Factory Physics" [23] suggests that there should be some connection. In fact, it is quite natural to study production and logistics from the point of view of material flows [14]. Therefore, many-particle approaches such as Monte-Carlo simulations and fluid-dynamic models [8, 15, 31, 2] should be applicable to logistics systems. As we will discuss in the following, this is really the case.

Our contribution is structured as follows: In the first part (Sec. 2) we highlight some sources of complex dynamical behavior in logistic systems and discuss the impact and implications of these mechanisms. In particular we address the nonlinearities in material flow processes (Sec. 2.1), caused by control algorithms. Moreover, the dynamics induced by connecting several logistic sub-systems in networks has itself important influence and may lead to complex dynamics and instabilities, even if a single subsystem behaves stable and regular (Sec. 2.2). Thirdly, we discuss phenomena like the "slower is faster effect" emerging due to nonlinear interactions in many particle systems as they are regularly found in transport systems in logistics (Sec.2.3).

The second part of this paper, i.e. Sec. 3, introduces two basic control principles, which may improve the controllability of complex logistic systems.

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On the one hand side, system wide coordination by means of synchronization can be reached by a local coupling of neighboring control elements, while centralized control is not necessarily required (Sec. 3.1). But also by establishing suitable local interaction mechanisms local coordination may eventually spread all over the system (Sec. 3.2). Both principles benefit from the interesting features of self-organizing systems: based on nonlinear interactions, a locally emerging pattern may have global effects.

2 Sources of Complex Behavior in Logistic Systems

Modern logistics systems inside a factory as well as the corresponding logistics systems for supply and distribution are typically large networks of various production and storage facilities. Their dynamics is governed by complex, system immanent inter-dependencies involving both deterministic and stochastic elements as well as unforeseen external influences. In certain regards logistics and production networks may be described as coupled dynamical queuing systems. Considering discontinuities in the processes and a generally non-synchronous flow of material and information in network like systems, modeling an understanding of the dynamics of these complex systems is challenging. The traditional approaches to queuing systems focusing mostly on equilibrium solutions or computationally costly discrete event simulations are limited if it comes to larger systems. Moreover, usually a huge number of non-stationary system components, e.g. for transport tasks are included in logistic systems. Thus logistic systems, in particular transportation systems, fit into the class of multi particle systems which reveal a number of quite surprising dynamical properties [13].

In the following we shall discuss typical sources of complex behavior in logistic systems and recent approaches to modeling and understanding of the related complex dynamical behavior.

2.1 Discontinuities in Processes

Production and supply processes are usually not constant in time. Weekly and seasonal cycles, for example, generate oscillatory behavior. However, a closer look at logistics systems uncovers, that within a logistics process several material flows (i.e. different products and educts) will interfere at nodes of logistics networks. These nodes may be workstations in production or warehouses and terminals in supply networks where material flos compete for scarce resources (capacities, time, vehicles, ...). For the majority of all logistic systems a parallel service of several intersecting flows or conflicting tasks is impossible, unsafe or inefficient. Alternating exclusion of conflicting tasks is frequently required in the organization of production processes, road traffic or in communication networks. Instead of parallel processing a sequential switching between different tasks must be organized (see Fig.1).

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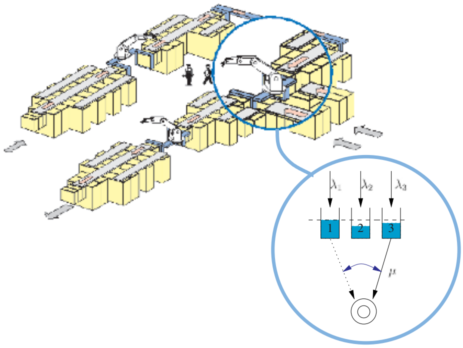

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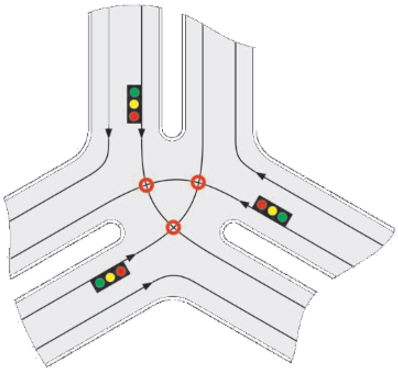


b)

Fig. 1. Situations, where conflicts in the service of different material flows at intersection points must be resolved are common in logistics networks.
(**a**) Illustration of a production system in which a robot has to serve three different processes. Such switched server systems can be understood as hybrid dynamical systems: We have different buffer queues which are continuously filled with materials but only one of the buffers can be emptied at a time. Moreover, switching between containers takes a setup time τ^{setup}. Therefore, switching reduces service time and is discouraged (after [32]).
(**b**) The same situation occurs in traffic networks. At a single intersection the service, i.e. the green light of corresponding traffic lights is switched between the different lanes to allow all vehicles to cross the intersection without conflicts. While switching from one state to another, all traffic lights are set to red for a period of τ^{setup}

If we consider logistics systems as dynamic systems, control related switchings between different operation modes and parameters are essential nonlinearities leading to complex behavior in these systems. At a reasonable level of abstraction it is possible to neglect stochastic influences and to approximate the material flows as a continuous flows. This approach leads to models of dynamical systems consisting of piecewise defined continuous time evolution processes interfaced by some logical or decision making process. These systems have to be described by continuous as well as by discrete (logical) variables in the framework of hybrid dynamical systems.

Figure 2 illustrates a system in which a robot has to serve three different processes. Such systems can be mapped to so-called switched server systems: Let us assume we have different buffers which are continuously filled with material at certain rates. All buffers have finite storage capacity, and only one buffer can be served at a time. Moreover, switching between different buffers

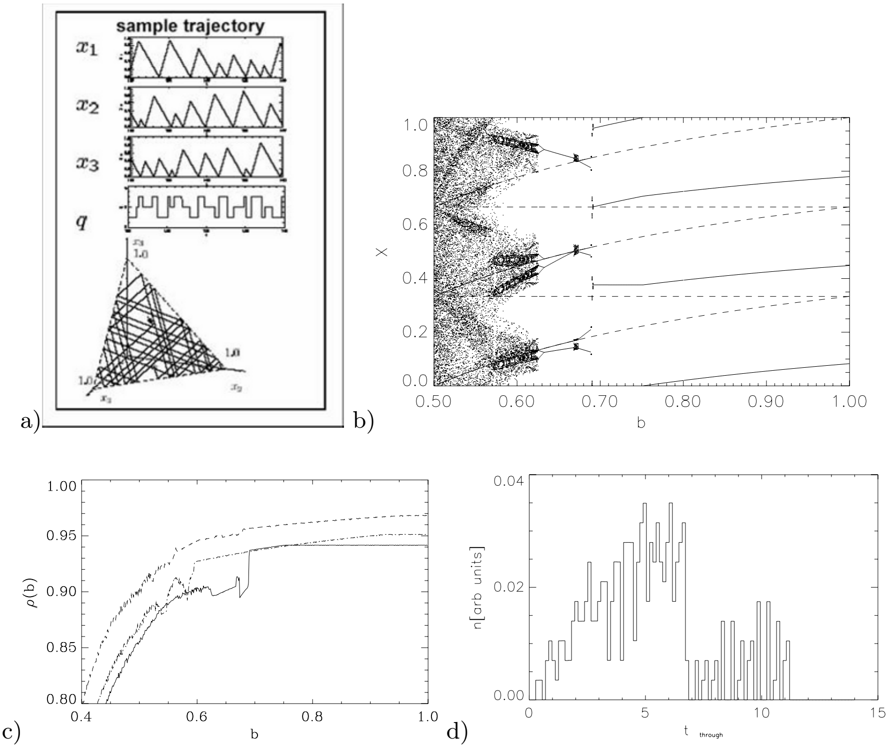


Fig. 2. Illustration of a switched server model . The graphics (**a**) on the right illustrates the strange billiard dynamics of the trajectories, which is often chaotic. By changing the capacity b of buffers, different dynamic behavior of the system is induced, as depicted in a bifurcation diagram (**b**). The dynamics directly determines the reached throughput rate $\rho(b)$ of the manufacturing system (**c**). Note, that a lossless production will result in $\rho = 1.0$ and the restricted capacity of buffers can dramatically decrease the throughput, and even induce surprising jumps in the production rate (The different curves correspond to different feeding rates of the input buffers.). The dynamics determines also the distribution of throughput-times, which can be multi-modal even for such relatively simple systems, as the histogram (**d**) depicts (after [31])

or different products, respectively, takes a setup time. Therefore, switching reduces service time and is discouraged. As a consequence, one may decide to empty the currently served container completely and then switch to the fullest container in order to avoid that its capacity is eventually exceeded. However, if the capacity of any buffer is reached before an other product buffer is served completely, the service of the latter must be interrupted to serve the filled buffer anyway. Such a control algorithm (which is usually implemented in form of priority policies in production systems) leads, if mapped to the state space of the system, to a strange billiards kind of dynamics (i.e. trajectories reminding of billiard balls reflecting at some non-rectangular boundaries). These dynamics can be investigated by considering the mapping of boundary points onto other boundary point under the dynamics of the system. Depending on the properties of this mapping it may easily happen that this dynamics tends to be chaotic [32, 31] (see Fig. 2). In particular, production speeds for different product and the capacities of buffers or material flow relations are crucial parameters, which play the rule of bifurcation parameters in the dynamic system. If critical parameters values are reached or crossed, the dynamic behavior of the system can, according to bifurcation theory fundamentally change, often unexpected.

Moreover, the complicated, even sometimes chaotic dynamics has implications for the relevant performance metrics of manufacturing and logistics. Depending on the dynamic regime, throughput times and their distributions, for instance, are changing. For this reason, many statistical distributions of arrival or departure rates may actually be a result of non-linear interactions in the system. The complex dynamics has important consequences for the system, making it difficult to predict the future behavior and process times. This complicates control a lot. Moreover, non-linear interactions often imply (phase) transitions from one dynamical behavior to another one at certain critical parameter thresholds. Such transitions are often very unexpected and mix up the schedules. We actually conjecture that the phase space (i.e. a representation of dynamic behaviors as a function of parameter combinations) is in many cases fractal, i.e. subdivided into small and often irregularly shaped areas. An understanding of such systems requires a solid knowledge of the theory of complex systems. For this reason, production and logistics are interesting areas for fundamental and applied research of theoretical physicists. We should particularly underline that, due to the many parameters in production systems (e.g. production speeds, minimum or maximum treatment times in time-critical processes, etc.), the sensitivity to (even small) parameter changes is mostly large. Therefore, the performance for a new combination of parameter values is only poorly estimated by interpolation between previous experimental measurements, which are usually available for a few parameter sets only. That is, the predictability and robustness of production processes is often low, while they are an important aspect for efficient and reliable production.

2.2 Network Effects

Several previous works uncovered a variety of oscillatory and even chaotic behavior in production systems and supply chains [25, 32, 17, 36]. Whereas traditional modeling approaches focused on stochastic queuing models recently the formulation of continuous flow models for the information and material flows in supply networks lead to new insights. By formulating the dynamics of warehouses or suppliers in a supply network in form of coupled differential equations by denoting the inventory of a node j in the supply chain as

$$\frac{dN_i}{dt} = Q_i^{\text{in}}(t) - Q_i^{\text{out}}(t) = \underbrace{\sum_{j=1}^{u} d_{ij} Q_j(t)}_{\text{supply}} - \underbrace{\left[\sum_{j=1}^{u} c_{ij} Q_j(t) + Y_i(t)\right]}_{\text{demand}} . \qquad (1)$$

Here u production units or suppliers $j \in \{1, \dots, u\}$ deliver d_{ij} products of kind $i \in \{1, \dots, p\}$ per production cycle to other suppliers and consume c_{kj} goods of kind k per production cycle. The coefficients c_{kj} and d_{ij} are determined by the respective production process, and the number of production cycles per unit time (e.g. per day) is given by the production speed $Q_j(t)$. That is, supplier j requires an average time interval of $1/Q_j(t)$ to produce and deliver d_{ij} units of good i. The above formulation allows for an investigation of supply chains in terms of the stability theory for dynamical systems. In particular the influences of different supply network topologies, which enter into the model via the supply matrix d_{ij} are accessible for a mathematical analysis.

Helbing et al. [17, 21, 22] found both convective and absolute instabilities in continuous models of supply chains, which induce in certain parameter regions increasing oscillations along a supply chain. These observations may explain the so called bull-whip or Forrester-effect from first principles. The investigation reveals additionally, that sometimes even small changes in the supply network topology can have enormous impact on the dynamics and stability of a supply network.

The results of such models may therefore allow for a systematic approach to the design of robust supply networks under dynamically changing demands.

2.3 Dynamic Interactions and “Slower is Faster” Effects

One characteristic feature of driven multi-component or driven many-particle systems operated near capacity is the possibility of mutual obstructions due to competition for scarce resources (time, space, energy, etc.). From game theory it is known that the selfish, local optimization of the behavior of all elements can lead to system states far off the system optimum. That is, even if all parts of the system perform well and serve the local demands best, the overall result can be very bad. This is obviously the case, if the different processes are not well synchronized or coordinated otherwise. Therefore, it can be better to wait for some time rather than starting activities immediately upon availability. Such actionism could produce overcrowding, bottlenecks, and inefficiencies in other parts of the system. We will illustrate this, sometimes rather surprising effect for different examples of transport and production systems.

Slower is Faster Effects in AGV Systems

Nowadays material transport within nodes of logistic networks, such as warehouses, manufacturing systems or logistics terminals, is often done by automated guided vehicles (AGV), i.e. without any drivers. These vehicles move along virtual tracks. We have studied such a logistics system, namely a container terminal in a harbor. There, containers had to be moved from the ships to the container storage area and back (see Fig. 3). However, instead of moving most of the time, they often obstruct each other. This is, because each

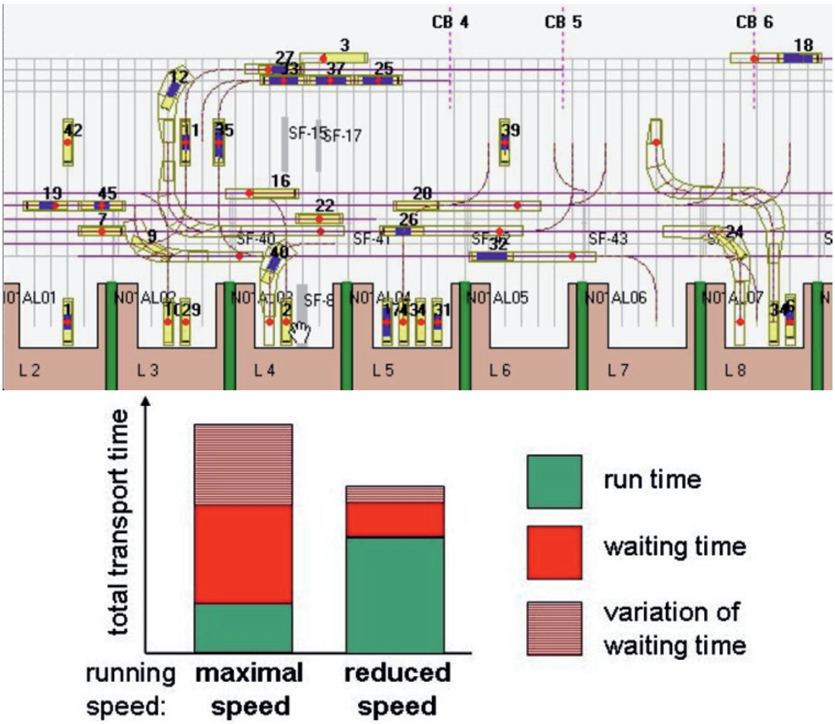


Fig. 3. Top: Illustration of a container terminal in a harbor. The containers are moved by automated guided vehicle along virtual tracks. **Bottom**: The total transport time is composed of the run time and the waiting time, which varies a lot. Furthermore, it strongly depends on the vehicle speed

vehicle is surrounded by a safety zone, which may not be entered in order to avoid accidents and damage of goods.

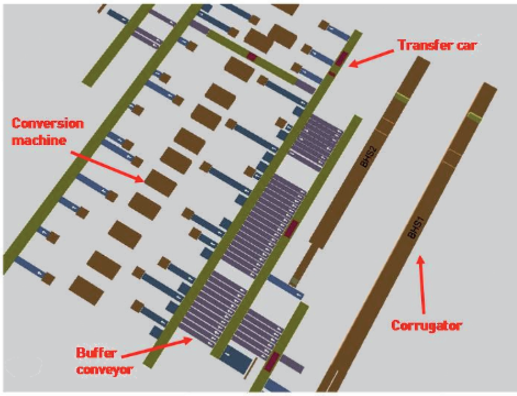
According to the "slower-is-faster effect" , the logistic processes may be more efficient, if the speed of the automated guided vehicles is reduced. In fact, there should be an optimal speed. Reducing the speed will, of course, increase the run times. However, it also allows one to reduce the safety zones, since these are essentially proportional to the speed. As a consequence, the vehicles will not obstruct each other so often. Thus, their waiting times will go down. Moreover, the predictability of the whole system is improved due to the reduced fluctuations, such that also the scheduling of transport jobs has to deal with smaller safety margins. These effects can overcompensate the increase in the run times. Therefore, reducing speed can sometimes make logistic processes more efficient.

Dynamic Interactions and the Optimization of Buffer Loads

A similar observation can also be made in storage units with automated material handling systems. Here we refer to a production layout which can be found in many industries as for instance the packaging industry. We consider a two stage manufacturing process, where the different stages are decoupled by an automated storage area which serves as buffer. In some factories producing packaging materials (see Fig. 4), the most expensive machine, the corrugator, brakes down quite frequently, if it is not new anymore. The corrugator produces the packaging material (corrugated paper), i.e. the basic input for all other machines. Therefore, the breakdowns are usually considered as causing the main bottleneck and limiting the profitability of the factory. As a consequence, the corrugator is often run full speed whenever it is operational.

Potentially, this causes earlier breakdowns, which could be avoided by a lower speed of operation. Moreover, it also produces congestion in the buffer system. Whenever the system exceeds a certain utilization ("work in process"), so-called cycling procedures are needed to find the stacks which were required for further processing (see Fig. 4). These cycling procedures take over-proportionally more time, when the buffer system becomes fuller. In this way, the buffer operations become quite inefficient. As a consequence, the real bottleneck is the buffer system.

In principle, there are two ways to solve this problem: Either to increase the buffer storage capacity or to stop the corrugator, when the buffer system reaches a certain utilization (see Fig. 5). While the corrugator is turned off, it can be cleaned and fixed. This proactive maintenance can reduce the number and duration of unplanned downtimes. Therefore, reducing the speed of the system increases its throughput and efficiency again. Our event-driven, calibrated simulations of the production system indicate that the expected increase of production efficiency would be of the order of 14%.

a) 

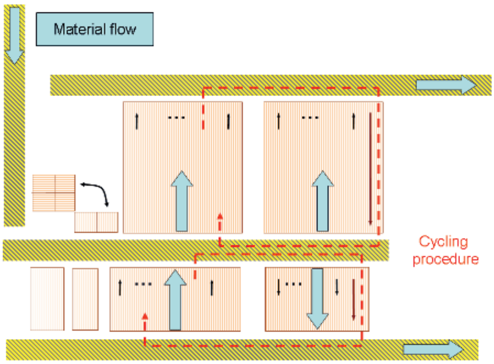
b) 

Fig. 4. Top: Illustration of a plant in the packaging industry producing boxes. The corrugator produces corrugated paper board, which is processed (e.g. cut and printed) by conversion machines. Transfer cars transport the materials, and buffers allow for a temporary storage.
Bottom: Illustration of the cycling procedure, by which a specific stack is moved out of the buffer for further processing. This procedure can be quite time-consuming, if there is a lot of work-in-process (WIP) in the buffer

3 Self-organization in Complex Systems as a Possible Control Paradigm

Besides the dynamical phenomena discussed above, the optimization of production processes is often an NP-hard problem . For this reason, it is common to use precalculated schedules and designs determined off-line for certain assumed boundary conditions (e.g. given order flows). This is mostly done with methods from Operations Research (OR) or event-driven simulations. However, in reality the boundary conditions are varying in an unknown way, so that the outcome may be far from optimal, as the optimal solution is

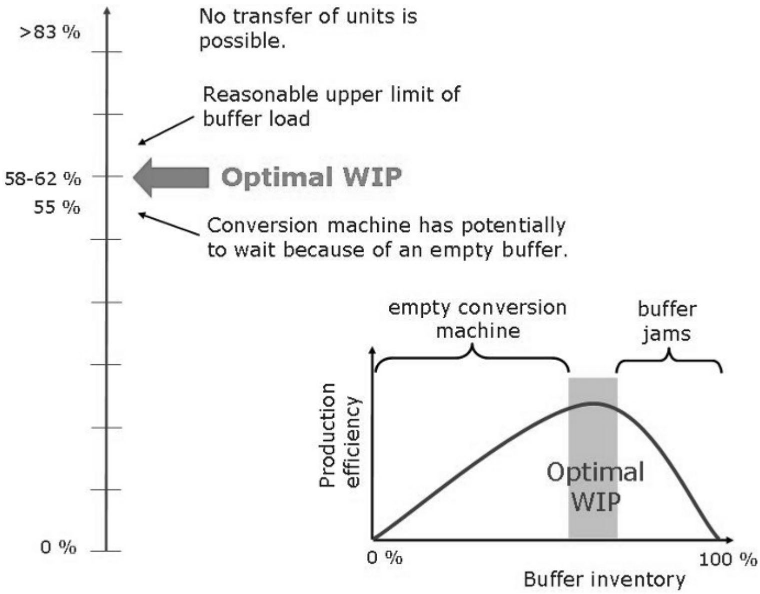


Fig. 5. Top and **middle**: The optimum buffer utilization is neither close to zero nor close to capacity. In the first case, the buffer may be emptied, so that further production steps are delayed. In the second case, buffer operation becomes inefficient or even almost impossible. In the illustrated practical example, the optimum buffer utilization is between 58% and 62% (only!). Stopping further transfer to the buffer at this level is reasonable and allows for proactive maintenance of the upstream production machine(s). According to computer simulations, this strategy is expected to reach a reduction in production times

sensitive to parameter changes (see Sec. 2). Therefore, adaptive on-line control strategies would be desirable. Although they cannot be expected to be system-optimal, the higher degree of flexibility promises a higher average performance, if the adaptation manages only to drive production *close* to the system optimum.

As the exact system optimum can mostly not be determined on-line, one needs to find suitable heuristics. Typical and powerful heuristic methods are, for example, genetic or evolutionary algorithms. However, their speed is also not sufficient for adaptive on-line control. Therefore, we are currently seeking for better approaches that make use of characteristic properties of material flow systems such as conservation laws. A typical example is the continuity equation for material flows. Such equations can also be formulated for merging, diverging, and intersecting flows, although this is sometimes quite demanding. Moreover, most of the logistic material flow networks are subject to continuous demand variations and unforeseen failures. Besides adaptivity and optimality, robustness and flexibility are important requirements for control concepts.

Can we learn from the stable, smooth, and efficient flow of nutrients and other chemical substances in circulatory systems of biological organisms? Synchronized dynamics of a population of cells often plays an important role for it [35, 41]. For example, our heart functions as an pump through the appropriate synchronized dynamics of a population of cardiac cells. This synchronization is realized through appropriate designs of cardiac cells and their network architecture of local interactions. Another interesting example is found in amoeboid organisms [29, 40], where the rhythmic contraction pattern produces streaming of protoplasm. Synchronization phenomena have been intensively studied for these biological systems during the last decades by means of mathematical models, in particular coupled phase-oscillator models [4, 12, 24, 35, 39].

3.1 Bundling Effects and the Synchronization of Switching Controls

Let us consider at first the problem of coordinating the switching between conflicting flow directions in a material transport network, which is a directed graph with of a set of nodes and links. Material can move between the nodes with a finite velocity. Thus any moving element experiences a delay t_{ij} between its departure at one node i and its arrival at the next node j. Whereas a distinct subset of nodes may act as a source or sink of moving material, we shall concentrate on those nodes where the flow of material is conserved, i.e.

$$\sum q^{\mathrm{in}} = \sum q^{\mathrm{out}}. \tag{2}$$

Here $\sum q^{\mathrm{in}}$ and $\sum q^{\mathrm{out}}$ denote the average rate of incoming and outgoing material, respectively. Each node has to organize the routing of materials arriving through incoming links towards its outgoing links. All allowed connections between incoming and outgoing links can be described through discrete states of the respective node. As long as such a state is 'active', material can flow from a subset of incoming links through the node and leave through outgoing links. All other flow relations are blocked. Usually the switching between different discrete states needs a certain time interval τ, called switching- or setup- time. Depending on the flow rates, the duration of these discrete states may vary.
A major simplification of the problem can be obtained if we consider a cyclic service sequence, we can assign a periodic motion to every switching node. Thus, a node can be modeled as a hybrid system consisting of a phase-oscillator and a piecewise constant function M that maps the continuous phase-angle $\varphi(t)$ to the discrete service state $s(t)$, e.g. $M : \varphi(t) \rightarrow s(t)$.
The switched service of different flows leads to convoy formation processes. This implies highly correlated arrivals at subsequent nodes, which requires to optimize M with respect to a minimal delay of the material. Whereas the map M can be optimized according to the actual local demand, the phase-angle φ is coupled to the oscillatory system of the neighboring nodes. Thus with a suitable synchronization mechanism we can achieve a coordination of the

switching states on a network wide level. In consequence we suggested in a previous paper [26] an adaptive decentralized control concept consisting of two parts:
(a) Phase-synchronization of all oscillators in the network, based on local coupling between intermediate neighbors.
(b) Mapping of phase-angles to the switching states based on local optimization.
For the sake of concreteness, we applied our method to the control of traffic lights at intersections of road networks. The objective of our decentralized control method is the network wide coordination of the individual switching sequences based on a local coupling between the intersections in the road network. By modeling each intersection i as an oscillator, characterized by its phase-angle φ_i and its effective frequency $\omega_i = \dot{\varphi}$, coordination is achieved by synchronizing the oscillator network. Hereby, for providing a common time scale and allowing the intersections to trigger the switching cycles right at the best time, we used a phase-locked state where the phase difference between neighboring oscillators is fixed [35].

Therefore we applied a coupling between any oscillator $i = 1, 2, \dots N$ and its nearest neighbors $j \in \mathcal{N}_i$ with adjustments of phases and frequencies on two different timescales.

Figure 6 shows a simulation of the control concept developed in [26]. Adaptive traffic light synchronization is an example for a potentially self-organized coordination among locally coupled service stations. The fraction of green lights for the east-west direction in a Manhattan-like road network varies in an oscillatory way, as expected. However, in contrast to precalculated traffic light schedules, the oscillations are adaptive and provide a flexible response to the local, stochastically varying traffic situation. The travel times of vehicles traversing a regular lattice road network are reduced due to a network wide coordination of traffic lights.

3.2 Congestion and Adaptive Re-routing

However, many times, materials can be processed by multiple machines with different technical and performance specifications. In the simplest case, one has I identical machines for parallel processing. The question is, which stacks should be sent to what machine? Therefore, if different alternative production paths are available, adaptive routing is an issue (see Fig. 7). Due to the finite setup times, it is normally not reasonable to send different stacks of the same job to different machines. Moreover, depending on capacity utilization, it may be costly to use *all* available machines. Obviously, the optimum usage of parallel processing capacity must be load dependent.

Here, a biologically inspired approach can help. When the trails are wide enough, ants are known to establish one path between the nest and a single food source. After some time, this path corresponds approximately to the shortest path. This means a minimization of "transport costs", i.e.

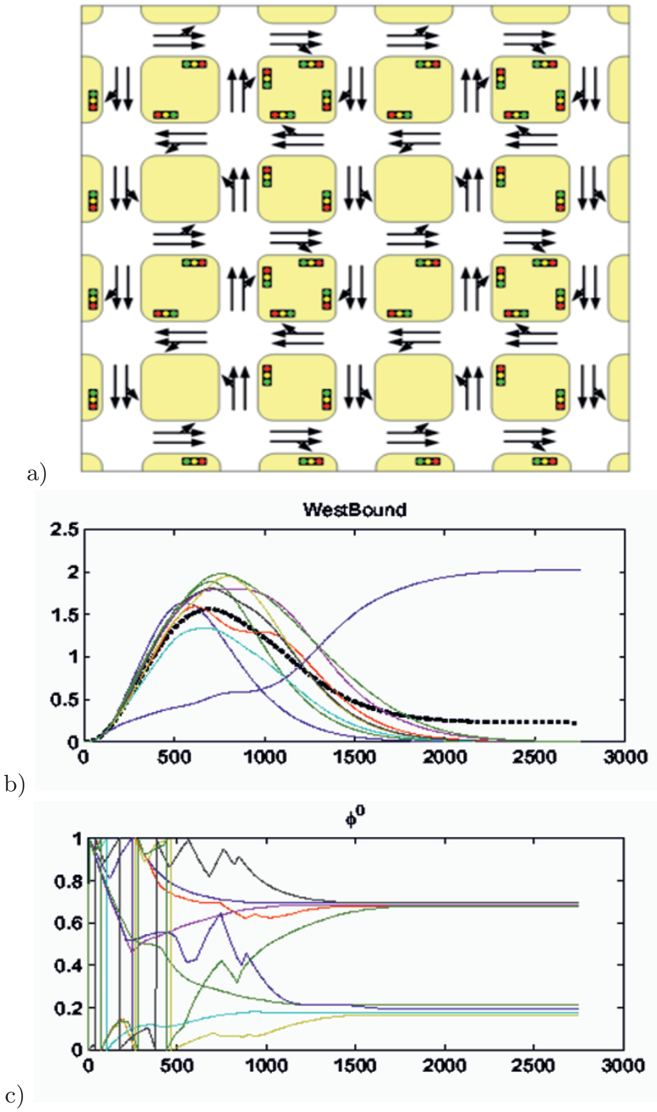
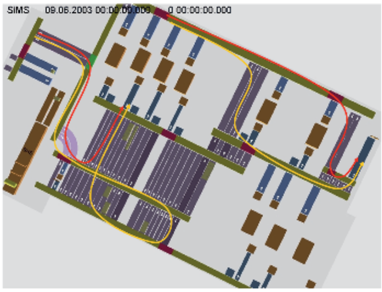


Fig. 6. The travel times of vehicles traversing a regular lattice road network (**a**) are reduced due to a network wide coordination of traffic lights. From a random initial state, the decentralized adaptive control concept let the intersections exponential convergence towards a globally synchronized state (**b,c**). Both, the synchronized cycle times as well as the locally adjusted switching states, allow the emergence of green waves and the reduction of overall travel times



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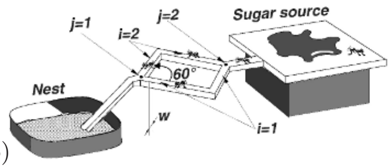

b)

Fig. 7. The choice between different available alternative ways in crowded situations occurs both in production and traffic, as well as in natural systems. Ants are able to adapt to this situation by a simple, local interaction mechanism.
a) Illustration of different routing options for material flows in a packaging factory. **b**) Illustration of an experiment on the route choice behavior of ants. Neither of the two branches of the bridge from the nest to the food source provided enough transport capacity alone. Although the chemical attraction is in favor of one ant trail only, repulsive pushing interactions can lead to the establishment of additional trails, if the transport capacity of one trail is too low (after [11])

optimum usage of resources. The underlying mechanism is a random exploration behavior in combination with a pheromone-based attraction via particular chemicals, which leads to a re-enforcement of the most utilized trails. In the end, one of the trails survives, while the others fade away.

It is interesting to see what happens if the capacity of the ant trail is too small to keep up the desired level of material flow (food). This has been tested by connecting nest and food source by two narrow bridges only [11]. In such cases, ants are using additional trails to keep up the desired level of throughput. The underlying mechanism is a repulsive interaction among ants. In an encounter of two ants at a bifurcation point, an ant is likely to be pushed to the alternative bridge. This can lead to the establishment of additional and stable ant trails [11, 33, 34] (see Fig. 7).

The microscopic simulations support the conjecture that the discovered collision-based traffic optimization principle in ants generates optimized traffic for a wide range of conditions. It optimizes the utilization of available capacities and minimizes round-trip times. Simulation results for a symmetrical bridge with four branches is shown in Fig. 8. It can be seen that the majority of ants uses one of the large branches, and within both branches, the majority of ants uses one of the small branches. Which of the branches is preferred basically depends on random fluctuations or the initial conditions. When the overall ant flow is increased, the ant flows on the branches become more equally distributed. Above a certain overall flow, the usage of the bridge is completely symmetrical, as for a bridge with two branches. On a

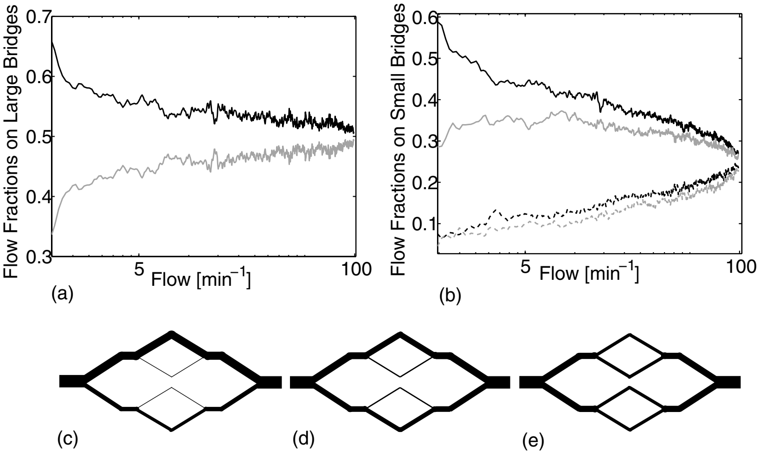

Fig. 8. Simulation results for a completely symmetrical bridge with two large branches that are again subdivided into two small branches each. The overall width of the bridge (i.e. all branches) is the same everywhere. (**a**) Fraction of ants on the two large branches as a function of the overall ant flow ϕ. (**b**) Fraction of ants on the four small branches. The lower figures give a schematic representation of the distribution of ant flows over the large and small branches (**c**) at very low flows, (**d**) at medium flows and (**e**) at large flows. (After [34])

logarithmic flow scale, it appears that we do not have a discontinuous transition from the use of one small branch to the use of two small branches and another transition to the use of three or four branches. However, the sharpness of the transition is certainly a matter of the choice of parameters.

Therefore, optimal machine utilization could be implemented via an ant algorithm [9, 3]. When the utilization (demand) is low, just one of the machines would be operated. Otherwise, based on suitably defined repulsive interactions, jobs would be distributed over more alternative machines or routes, depending on queue lengths and capacities.

4 Summary and Outlook

In this chapter we discussed sources of complexity in logistics networks. Considering the importance of a well functioning and effective logistics for our modern society and the wealth of their citizens the importance of new methods for understanding and optimizing of these systems can hardly be underestimated. As we have shown, the science of complex systems, including nonlinear dynamics, the study of network properties and many particle or traffic physics can help in this regard.

In the light of the complexity related point of view, optimization and control of logistics networks tends to be a challenging task. Therefore, new heuristics are needed to reach an adaptive, but highly performable operation. In this respect, we favor a *self-organization* approach. It requires a suitable design of the interactions in the system, otherwise it easily ends up in a local optimum or becomes unstable, such that breakdowns and slower is faster effects occur.

Biologically inspired methods are a promising approach, here. We have mentioned ant algorithms and synchronization principles, but learning from biology may also include the study of the production of artifacts in biological systems like cells and tissues and the transfer of biological organization principles to production plants and supply networks. In fact, this field, recently referred to as *biologistics* in Ref.[14] can foster a significant advancement in our ability to cope with the increasing complexity of logistics networks.

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