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Detecting Deterministic Chaotic Inter-arrival Times in Material Flow Systems

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Abstract

Automated, modular, asynchronous and locally controlled material flow systems promise high routing flexibility in production lines because their conveying modules can be reconfigured without reprogramming PLCs. However, if such material flow systems comprise cycles and different routes, they may exhibit undesirable deterministic chaotic inter-arrival times, which can lead to conveying bottlenecks when approaching maximum capacity. Since existing analytical models have not been practically adopted for planning material flow systems, an approach for detecting deterministic chaotic inter-arrival times during production is proposed. It employs the Hough transform to identify trajectories in inter-arrival time phase space. The approach is tested with a laboratory double belt conveyor system, in which non-deterministic behavior is minimized. Results are compared with a previously published analytical model. It is shown that the proposed approach is able to detect deterministic chaotic inter-arrival times for the test cases. Phase trajectories are only partly identified. Future research should test and compare different line detection algorithms for their influence on the approach's robustness in practical production environments.

Keywords

Assembly control; Material-flow; Discrete event systems; Time complexity; Automation

1. Introduction

In series production of piece goods, material-flow automation is a common approach to reduce non-value adding labor cost. This approach considerably affects production efficiency because the time of material handling is a considerable part of total manufacturing time. Following [1], its ratio is about 85%.

A popular class of automated material transport systems employs double conveyor belts to transport work pieces that are located on work piece holders. Such systems support routing flexibility. Two conveyor belts are normally moving at constant speed and take work piece holders with them using friction. When a work piece holder encounters an obstacle, e. g. a stopper or another work piece holder that is already blocked, it stops while the conveyor belts continue to move underneath it. When the block finishes, the obstacle is removed and the work piece holder is again moved by the belts. For such conveyor systems, distributed control can be used to make them reconfigurable [2].

A typical layout of double conveyor belts comprises a main loop and several side loops, in which stations are situated. Each work piece holder contains a memory with its production plan and a pointer to its next production step. At each junction, the memory of an arriving work piece holder is read out e. g. via RFID. If a station that is viable for conducting the next production step is situated inside the side loop then - if possible - the work piece holder is routed to this side loop. Otherwise, it continues its journey in the main loop. This design allows decentralized control of the material flow system because a Programmable Logic

Controller (PLC) that is responsible for controlling one side loop does not require knowledge about the other side loops but may only communicate via the work piece holders' memories.

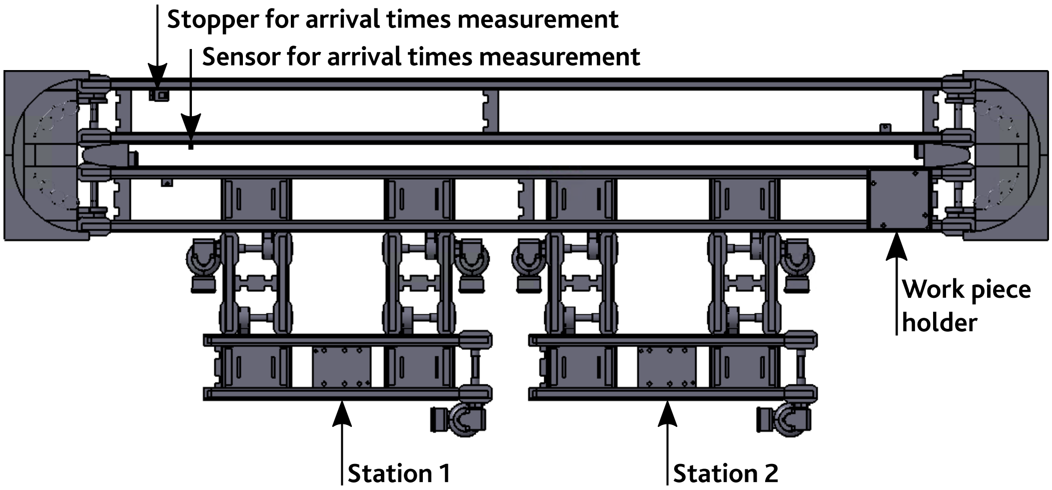

Figure 1: Double conveyor belt system with one work piece holder.

This control design allows reconfiguration of the material flow system layout without reprogramming PLCs, which can be considered an advantage for agile production (c. [2]). However, it also implies that the material flows through the different routes are normally not synchronized. It has been shown in [3] that such non-synchronized routes in material flows may lead to deterministic chaotic behavior, which may lead to reduced conveying capacity that can reduce overall production efficiency of assembly systems.

In practice, such state explosions are either ignored or they are counteracted with system designs that limit the number of system states but that are harder to reconfigure at the control level. Considering non-synchronized production systems or production system chains this approach becomes infeasible.

Relevance of chaotic behavior in production systems with loops has been reported by several researchers (c. [4] and [5]). While effects on efficiency may be dominated in systems with high down-time ratio, it can lead to conveying bottlenecks when approaching maximum capacity. Furthermore, deterministic chaotic behavior should be generally avoided because it introduces unlimited numbers of system states, i. e. dynamic complexity. In [6], it has been shown that stochastic effects such as processing time variability overlay but do not cancel this effect. Therefore, it would be desirable to detect such deterministic chaotic behavior when it happens during production in order to be able to counteract it e. g. by re-initialization. In [4], a mathematical model of autonomously controlled production networks considering time delay systems is described, which allows stability analysis using Lyapunov functions. However, practical management or control of the effect are considered hard because published models of the effect in [3] or [4] are difficult to understand and handle in engineering practice.

After a short overview of present approaches to material flow analysis, this work presents a novel, practically applicable method for automatic detection of deterministic-chaotic material flow behavior. The method provides a measure that describes the complexity of the trajectory that the inter-arrival times converge to in phase space. In this context, the term phase space is considered in the context of discrete event systems and shall be defined as a space of two dimensional vectors, where the first component is the n-th and the second component is the (n+1)-th inter-arrival time. In a proof of principle, the method is tested using a double belt conveyor system with two work stations that are situated in separate side flows. Stochastic behavior is minimized in the tests. Should the method prove applicable to real world scenarios, it could be used for on-line detection of chaotic material flow behavior in production systems.

2. Models of deterministic chaotic material flow behavior

2.1 Material flow simulation

Today, material flow simulation is an established technology that is widely adopted throughout industry (c. [7]). The dominant paradigm is to employ discrete event simulation models that are set up and parameterized in graphical user interfaces. Graphical definition of material flows and control flows are often accompanied by code that describes behavioral logic. An approach for reducing manual modeling effort has been proposed in [8].

Material flow simulation has been employed to investigate deterministic chaotic effects with limitless growing state space in [6]. It was found that deterministic chaotic effects overlay stochastic effect so that either may be dominant (s. Figure 2).

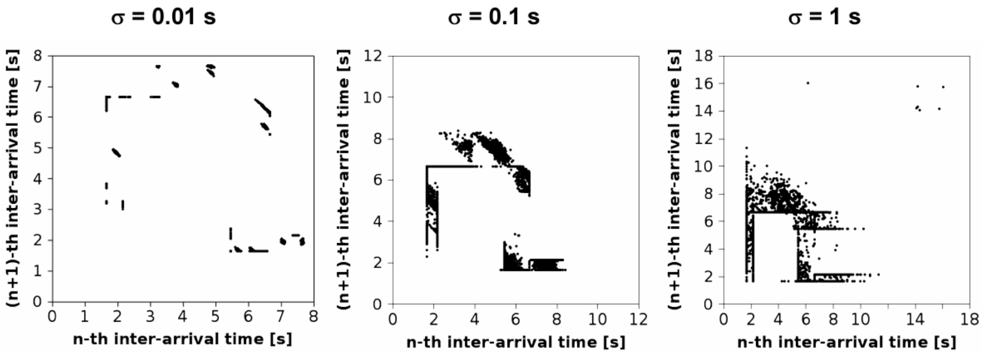

Figure 2: Simulated inter-arrival time patterns for normal distributed bottleneck station processing times with different standard deviations for a double belt conveyor belt system using 57 work piece holders [6].

A different approach is to employ physics simulation for material flow simulations to reduce modeling effort for the non-controlled environment behavior (s. [9]). Resulting motions are less abstracted than those of discrete event simulations. Therefore, accelerations can be investigated, which enables optimizing conveying velocities (c. [9]). [10] provides a survey of 3D game engines that comprise physics considering their application for production system simulation.

2.2 Analytical material flow models

A well researched domain of analytical approaches to model and analyze material flow behavior is queueing theory (s. [11]). There, arrival times are assumed to follow stochastic distributions. If complex layouts are considered, these distributions normally follow specific types such as exponential distributions (c. [12]).

Furthermore, colored Petri-networks (c. [13]) and max-plus dioids (c. [14]) have been employed for material-flow analysis of flexible manufacturing systems. Typically, in these analytical approaches deterministic chaotic behavior is ruled out by a-priori assumptions or by modeling rules that are required for applying model analyses.

In [3], series based analytical models for deterministic chaotic inter-arrival time behavior has been presented. However, practical applications of the approach are limited because an analytical measure for comparing or assessing the time series is missing.

3. Method for detecting deterministic chaotic inter arrival times

The main idea of the method is to treat scatter plots of the phase space of inter-arrival times, i. e. the plot of the n-th and (n+1)-th inter-arrival time as images, on which the probabilistic Hough line transform [15] is employed for line detection. If lines are detected then there are visible trajectories in phase space that indicate deterministic chaotic behavior. The number of lines is employed as an indicator of dynamic complexity.

As an input, the proposed method employs arrival times of work piece holders at a specific location in the main loop. This location is situated in the region in front of a fork joint that leads to a bottleneck station. In front of the location, there must be a queueable conveyor section (s. Figure 1). Since modern PLCs have access to an internal clock, detection of arrival times is easily implementable. However, for the method time accuracy is crucial so that the logging of arrival times should run in a fast loop that is separated from the main control program. The method's steps are conducted as follows:

- Arrival times are stored with a sampling frequency of 1000 Hz in a ring buffer of 100 values inside the PLC.
- Each 20 ms, the ring buffer is read out by a computer that is connected via field bus.
- After each read out, the new arrival times are converted into inter-arrival times by subtracting the previous arrival time.
- Each inter-arrival time is mapped to a 2D histogram with 100 bins for each axis (optimum bin size may vary for different systems), in which the x-coordinate represents the (n)-th inter-arrival time and the y-coordinate represents the (n+1)-th inter-arrival time.
- A binary matrix is set up, in which each element corresponds to a bin. Each matrix element is set to 255 for empty bins and to 0 for non-empty bins.
- The matrix is extended by 1/5 its size at each border, i. e. 20 elements are padded at the top, bottom, left and right border so that the matrix size becomes 140x140.
- The Canny edge detector [16] is applied to the matrix as it were an image.
- The probabilistic Hough line transform (s. [15]) is applied on the result.
- Resulting lines are counted.

Table 1 provides an overview of the parameters for the Canny edge detector and the probabilistic Hough line transform, which have been manually derived.

Table 1: Parameters for the algorithms

Algorithm	Parameter	Value
Canny	Gaussian filter kernel size (x and y)	10
	Hysteresis procedure threshold 1	100
	Hysteresis procedure threshold 2	200
	Sobel operator aperture size	7
Probabilistic Hough Line Transform	Distance resolution	20
	Angle resolution [rad]	0.17
	Voting threshold	50
	Maximum gap between points	30

4. Tests setup

The tests have been conducted with a Bosch TS/2+ based conveyor system (s. Figure 3). The double belt conveyor system comprises a main loop and two side loops. Processing times of both stations are 10 s. Conveying speed is 0.22 m/s. The production plan for each work piece holder is Station 1 → Station 2 → Station 1 → etc.

Figure 3: Test setup with double belt conveyor

The overall system is controlled by three independently operating PLCs (one for the main loop and one for each side loop). The main control program cycles of the three PLCs are not synchronized with each other. Arrival times measurements are performed independently on one PLC so that the PLC runs both the main control program and a measurement program with 1 ms cycle time.

Behavior at the joints follows one pattern that is commonly found in industry:

When a work piece holder arrives at a fork joint of a side loop with its next station then it is immediately routed into the side loop if possible. If the side loop is blocked because of a queue in front of the bottleneck station, the work piece holder waits for 4 s, during which it is routed to the side loop as soon as no block is present any more. If the block lasts longer then the work piece holder continues traveling along the main loop.

When a work piece holder arrives at a merge joint, the side loop always gets precedence so that blocking of the station inside the side loop is avoided.

Work piece holders are initially queued at the stopper behind the long outer section of the main loop (front conveyor right in front of the turning unit in Figure 3)

Tests are conducted with each number of work piece holder numbers starting at 1 and ending at 32. At 32 work piece holders, a deadlock immediately occurs. Note that deadlock situations start occurring at 26 work piece holders and above after less than one minute.

5. Results

For 1 to 7 work piece holders, all detected lines are situated close to the x and y axes, and no chaotic behavior can be observed. Note that for tests with 3 work piece holders or less, no lines are detected because of the maximum gap parameter employed.

Figure 4 visualizes the test results for 7 to 14 work piece holders. Doing a visual analysis, an increasingly relevant pattern that covers areas far from the axes emerges. The pattern is highly visible for 12 work piece holders and disappears in tests with 14 work piece holders and more. In the pattern, polygonal features are manually observable.

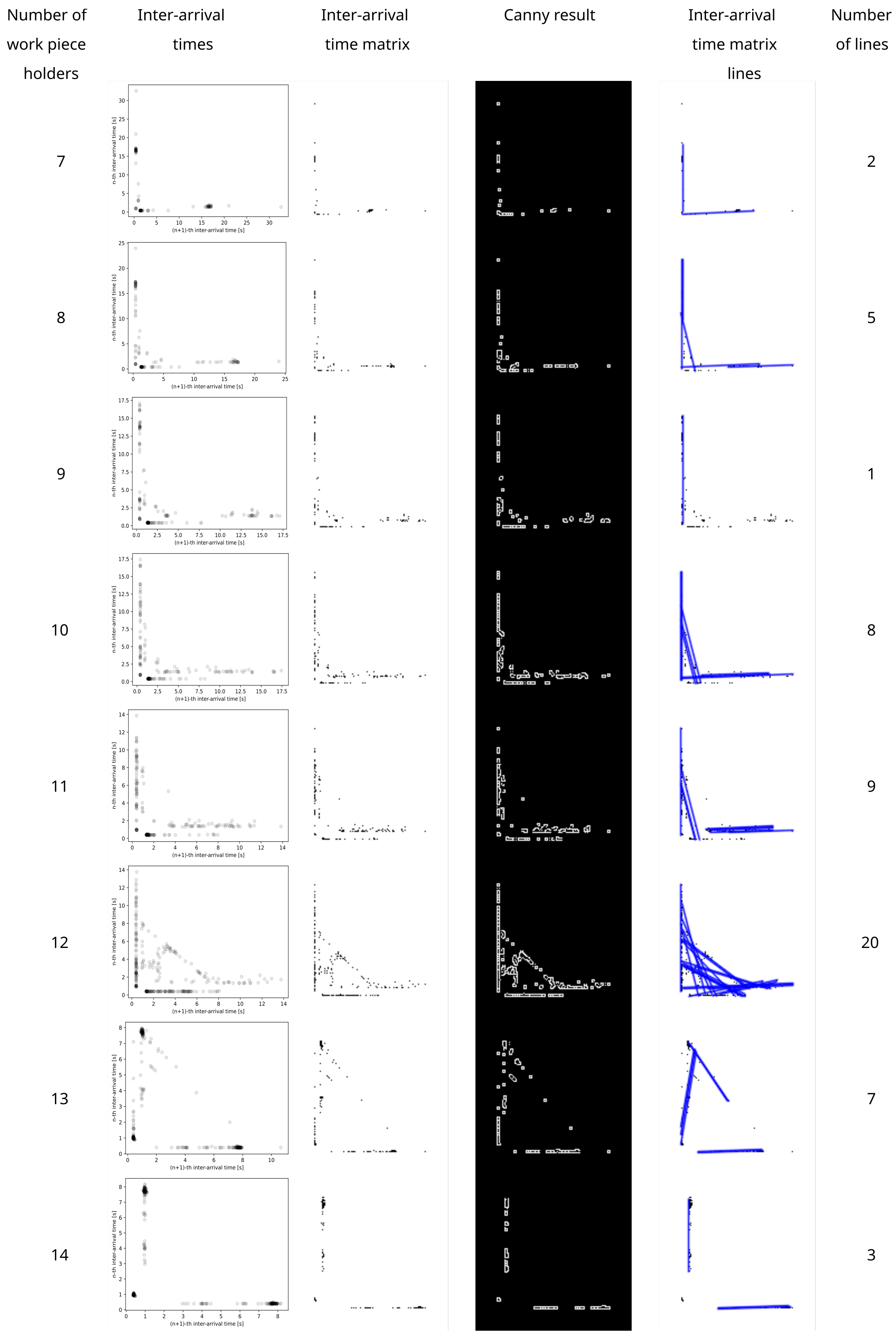

Figure 4: Test results after 15 min. The inter-arrival time matrix is derived from a histogram following Figure 2.

The lines that are detected by the method generally follow the visually observed patterns. However, more lines are generated than expected. In the case of 9 work piece holders, lines near the axes are not generated. Note that while line detection accuracy depends on the four parameters for the Probabilistic Hough Line Transform that are shown in Table 1, the most critical parameter has been the maximum gap between points. The result that the maximum number of generated lines clearly indicates the situation with the strongest pattern at 12 work piece holders is robust against parameter variations of less than ± 10% maximum gap between points.

6. Discussion

The proof of principle test demonstrates that for the considered scenario, the proposed method can be employed to automatically detect deterministic chaotic material flow behavior in double conveyor belts. The method and its algorithms that are state of technology in image analysis are able to extract lines that follow phase space trajectories.

However, while the number of detected lines grows with the convolution of the inter-arrival time pattern, the gaps in the pattern that remain after 15 min measurement time lead to misidentified lines. In the case of 13 work piece holders, lines are detected at the left side that go from bottom left to top right. Considering the other patterns, one would expect one line that is vertical and two parallel lines from top left to bottom right, which represent different routes through the system. These patterns become more dominant for longer test times. Effectively, the maximum gap between points parameters prevents correct detection of lines for the considered 15 min measurement time. However, reducing the maximum gap parameter results in a lower overall number of recognized lines to a point, in which the approach does not yield usable results. Therefore, the proposed approach is considered unsuitable for detecting root causes for deterministic chaotic behavior or for phase space trajectory reconstruction.

Nevertheless, automatic detection of chaotic behavior may provide insights for operative production management about system design shortcomings. The approach can easily be applied to existing conveyors e.g. by adding one proximity sensor per material flow loop. Employed at a large scale, it could draw attention to hidden issues that are normally covered by down times, breaks or idle times.

Besides its application using data from PLCs, the method can be directly applied to co-simulations e. g. in digital twins. Application in the design phase of systems would allow early checks for undesired deterministic chaotic behavior. As an addition to commonly used design quality checkers, the method could help to improve production system design.

7. Conclusion and Outlook

An approach for detecting deterministic chaotic inter-arrival times has been presented. In a test scenario, it has been shown to automatically detect patterns in inter-arrival time phase space. As a next step of research, the approach should be tested in real production situations that exhibit stochastic effects. If the results from the described laboratory test are reproducible in industrial production environments, the approach may help improve capacity flexibility by front loading issue handling. Instead of solving material flow bottlenecks that are caused by deterministic material flow chaotic behavior when production is maximized, detection may trigger a system or control redesign during normal operation.

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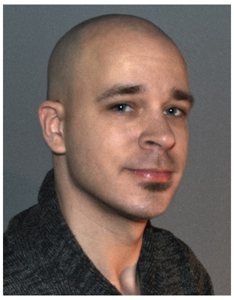
Biography

Martin Manns (*1975) has been head of the Chair of Production Automation and Assembly (FAMS) at the University of Siegen since 2016. Before his appointment, Univ.-Prof. Dr.-Ing. Martin Manns has worked in production research at Daimler AG (2009-2016) and Henkel KGaA (2007-2009) and as a post doctorate fellow at the University of Winsor, Ontario, Canada (2006-2007).



Denny Höhnen (*1989) is currently studying for his master's degree in industrial engineering and is also working as a research assistant for the Chair of Production Automation and Assembly (FAMS) at the University of Siegen. Prior to that, he completed a training program to qualify as a state-certified technical engineer (2013-2015) and graduated with a bachelor's degree in industrial engineering (2015-2020).