Modelling and analysis of an autonomous control method based on bacterial chemotaxis

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Abstract

Autonomous control intends to improve production systems' performance by a distributed and decentralised decision-making of logistic objects. This paper presents a bio-inspired approach for autonomous decision-making on the basis of the basic principles of bacterial chemotaxis movement. Similar to bacteria that orientate themselves according to a gradient of chemical attractants, intelligent logistic objects, e.g. (semi-finished) parts, are enabled to detect logistic targets offered by different alternative resources and to choose one of these. The relevance and impact of single decisions will be investigated for varying input parameters. Additionally, this method will be tested with the help of a computer simulation model of a shop floor scenario in order to investigate its performance in a complex production environment.

Keywords:

Production, Autonomy, Simulation

1 INTRODUCTION

During the recent years, customers have increasingly demanded highly customised products and the adherence to delivery dates has become critical. Present production planning and control systems cannot cope with this type of dynamics in an appropriate manner [1]. The implementation of new decentralised approaches, e.g. autonomous control, opens up new perspectives on coping with increasing dynamics. Autonomous control aims at the improvement of the logistic performance and a more flexible handling of dynamic complexity by enabling decentralised decision-making of intelligent logistical objects [2]. While centralized approaches are more advantageous in well defined and less dynamic situations, autonomous control performs better in complex and dynamic situations [3]. In the context of production logistics several bio-inspired autonomous control methods were developed [4-5]. This paper introduces a new bio-inspired approach, based on the concept of chemotaxis. The phenomenon of chemotaxis can be observed by bodily cells, bacteria, single cells or

multicellular organisms [6]. Chemotactic organisms direct their movement according to the concentration of chemicals in their environment. These chemicals are either attractants, like food substances, or repellents, e.g. toxic substances. In presence of an attractant the organisms start to move towards it. Depending on the chemical concentrations, this straight movement interrupts suddenly and the bacterium changes its direction randomly. Afterwards it starts swimming again. Due to this random movement it is able to find areas of high attractant concentrations [7]. These principles of chemotaxis were used in the past to generate heuristic optimisation algorithms, also called bacterial colony optimisation (BCO) or chemotaxis algorithm (CA) [8]. These approaches are often coupled with genetic algorithms [9]. Contrary, this paper presents an approach to transfer the process of chemotaxis to autonomous decision-making.

This paper is structured as follows: the concept of autonomous control is presented in section 2. Subsequently, section 3 gives an overview about of chemotaxis. These principles are transferred to an autonomous decision-making algorithm in section 4. The logistic performance of this method is evaluated in two steps in section 5. Within the first step, in section 5.1, decisions of single parts are analysed. An abstract model of a production system is introduced in section 5.2 for the purpose of analysing the new method. Finally, section 6 gives a summary and an outlook.

2 AUTONOMOUS CONTROL IN MANUFACTURING

Autonomous controlled logistic processes are characterised by a shift of qualified capabilities from the total system to its elements. In the context of production logistics for example, the decision-making process is transferred to single logistic objects, e.g. production orders, allowing these objects to route themselves through a logistic network according to their own objectives [2]. By interacting with other intelligent objects, these objects are able to gather information about current local system states and to use this information for decision-making [10]. Due to the interaction and decentralised decision-making, autonomous control may affect the logistic target achievement in a positive manner. The potential of autonomous control methods in production logistics was already shown in previous works [3-4]. Several autonomous control methods are inspired by biological processes, e.g. ant's or bee's foraging behaviour. Bio-inspired methods are characterised by a set of simple rules for autonomous decision-making and indirect communication of logistic objects [4-5]. These methods may improve the performance and the ability to cope with unforeseen events, e.g. machine breakdowns. Due to their differences, these methods affect the systems behaviour in different ways. Thus, the performance of autonomous control methods depends on the scenario. In this context new autonomous control methods may expand the portfolio of methods and help to cover a wider scope of scenarios.

3 NATURAL CHEMOTAXIS

This paper does not focus on reproducing the chemotaxis process exactly, but on adapting the basic principles. Thus the following will give a brief

description of a chemotaxis model with focus on the elementary mechanisms, which will be transferred to an autonomous control method. The movement mechanisms of the bacterium E. Coli are well-investigated. Its movement is caused by a set of flagella, which function as a motor. While turning all flagella in a clockwise direction, the bacterium performs a straight movement. This movement is interrupted by sudden phases of tumbling and reorientation. In these phases the flagella spin in reverse direction [7]. The probability of tumbling phases depends on the chemical gradient of attractants in the medium: In a neutral medium tumbling occurs in uniform intervals. In a medium with a higher attractant concentration tumbling occurs less and swimming phases last longer [6]. The detection of chemical substances and the internal cellular signal processing is done by a complex protein cascade. A simple model of this process describes this cascade as follows: An attractant activates a chemical receptor of the bacterium and starts the cascade: The activated receptor decreases in several steps the autophosphorylation of a protein named CheY. The motor complex, which causes the rotation of the flagella, is sensitive to the concentration of this phosporsiated form of CheY (CheYp) [7]. A change of CheYp concentration influences the probability of a sudden change of the flagella's rotation direction. This sensitiveness of the motor complex can be described by a sigmoid function [11]. A high concentration of CheYp causes a high probability of tumbling and vice versa. Due to this mechanism the bacterium detects changes of the attractant gradient. A detailed description of this adaptation process can be found in [6].

4 TRANSFER OF CHEMOTAXIS TO AUTONOMOUS CONTROL

Similar to bacteria, which can detect chemical gradients, an approach for autonomous decision-making can be designed. According to this idea objects are able to detect logistic targets offered by possible alternatives and chose one alternative based on the principles of chemotaxis. For example parts navigating through a production system have to decide for proper routes to achieve their targets (e.g., reduction of throughput time or the adherence to due dates). Each part decides about its route by using an iterative method shown in Figure 1, which emulates an imaginary chemotaxis process in a two dimensional space:

1) set start position y_0 randomly	
do while $x_n < X$	
2) determine actual gradient g on the basis of $A(Y_n)$	
3) calculate actual concentration of $CheYp(y_n)$ from gradient g	
4) determine tumbling probability P_k from $CheYp(y_n)$	
5) generate random number	
6) if (random number < tumbling probability) then	
true	false
generate new angle randomly	keep current moving angle
7) determine new x_n	
8) determine new y_n	

Figure 1: Pseudocode of the chemotaxis algorithm

The relevant logistic target value of each possible alternative is assigned to a relative *y* position. These target values are the equivalent of the concentration of food substances in the natural process. The *X* dimension denotes a certain predefined distance, which has to be passed during the iteration. The current position in the n^{th} iteration step is described by y_n and x_n. These positions are modified during the iteration, while the x_n position is smaller as the predefined distance ($x_n < X$).The result of this decision process is the alternative, which is assigned to the final y_n. Figure 2 (a) depicts exemplarily this process.

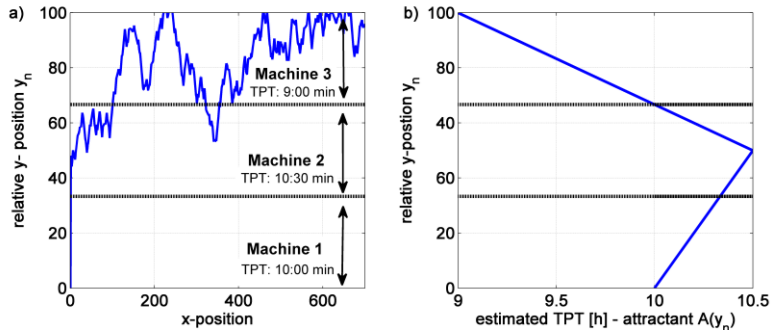

Figure 2: a) exemplary iteration process, b) corresponding $A(y_n)$

Figure 2a) shows this process for a decision between three different machines. The gradient between these machines is represented by the processing time or the estimated throughput time (TPT) of the machines. Figure 2b) depicts the corresponding gradient of target values. In this example the part chooses the machine 3 with the lowest TPT. The following describes the eight steps of the algorithm (in Figure 1) in detail:

In the first step a start position will be generated randomly and the gradient (step 2) is calculated. This gradient *g* depends on the current y_n, on the corresponding attractant concentration $A(y_n)$ and on the attractant concentration of the previous step $A(y_{n-1})$, respectively:

$$g\ y_n = \frac{A\ y_n}{A(y_{n-1})} \tag{1}$$

Therefore attractant concentration at a certain y_n position is modelled as linear function, which represents the differences in the target values (Figure 2 b). Based on this gradient the concentration of *CheYp* will be calculated in step 3 according to:

$$CheYp\ y_n = CheYp\ y_{n-1} \cdot \frac{A\ y_n}{A(y_{n-1})} = CheYp\ y_{n-1} \cdot g \tag{2}$$

As mentioned above, the concentration of *CheYp* affects in the natural process the activity of the motorcomplex. In the production logistic context it determines directly the probability of tumbling. Therefore *CheYp* is set into a sigmoid function in step 4. Here a logistic function is used, due to its sigmoid properties:

$$P_k \; CheYp(y_n) = \frac{1}{1 + e^{-k \cdot CheYp} \cdot (\frac{1}{P_0} - 1)} \tag{3}$$

In order to achieve a tumbling probability of 50% in case of a non changing gradient, the parameter P_0 is kept constant (P_0=0.5). Figure 3 depicts curves of P_k for different k. It shows that the probability for tumbling is less for smaller values of *CheYp*. On the other hand, the parameter k influences the slope of this function. Bigger values of k lead to smaller area of sensitiveness. The impact of k and the gradient g on the decision quality will be discussed later in section 5.1.

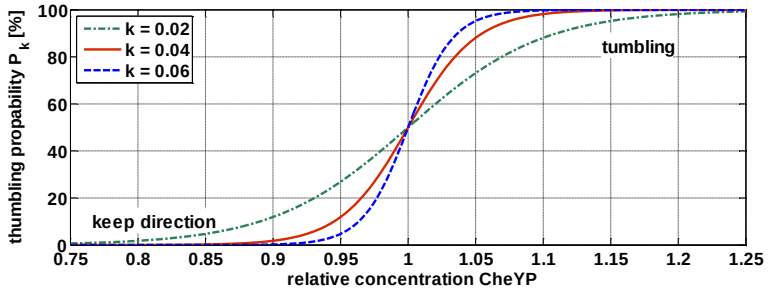

Figure 3: tumbling probability P_k for different k values

According to the calculated P_k the steps 5)-6) determine the direction for the next iteration step. If the random number is below P_k a new angle for movement will be generated randomly, else the current direction is kept. Finally new x_n and y_n positions are calculated. Steps 2)-8) will be repeated, until the predefined distance X is passed. After the iteration process the alternative of the final y_n will be chosen.

5 APPLICATION AND SIMULATION

The logistic performance of the chemotaxis method (CHE) will be analysed in two steps. In the first step the influence of the parameter k and the gradient g will be analysed in a simple production system with 3 different machines. Subsequently this method is implemented into a complex and dynamic shop floor model with 3x3 machines.

5.1 Performance of the CHE method on three different machines

A test environment with 3 machines is modeled. These machines offer different waiting times for a part, which has to choose one of these machines. The difference of waiting times is increased stepwise, so that the gradient g between the alternatives rises. The parameter k is also varied, which causes different sensitiveness of the probability function in equation (3). Each grid point of Figure 4 represents a single decision-making process of a part for different combinations of g and k. In order to reduce statistical effects, this is repeated 10^4 times and the percentage of decisions for the machine with the lowest waiting time is recorded as the

precision of the decision. Figure 4 depicts that a small gradient can be detected, by a sharp tumbling function, which is determined by a big *k* value. On the other hand for *k*=0.005 and *g*=2% only 30 % detected the machine with the lowest workload. Even if the gradient is bigger (*g*=100%) only 84% choose the machine with the lowest workload for *k*=0.005. Furthermore it can be noticed, that the ability to detect smaller gradients (*g*=2-10%) rises with the value of *k*. Hence bigger values of *k* lead to more precise decisions of autonomous parts.

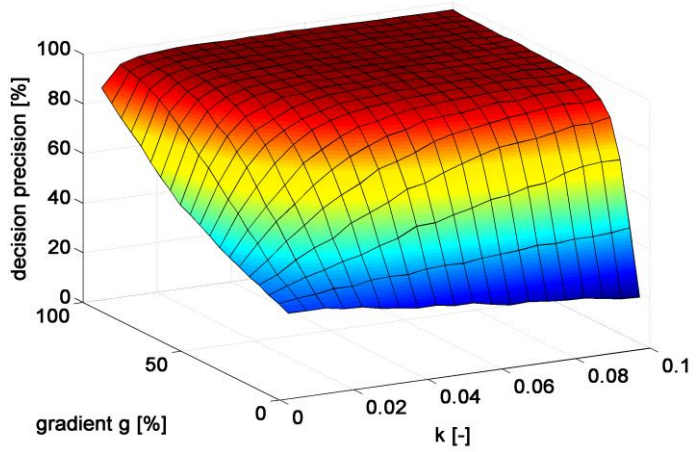

Figure 4: decision precision against gradient *g* and parameter *k*

Figure 4 shows that the precision of single decisions are influenced by the parameter *k* and the gradient *g*. In the next section the impact of both parameters on a more complex scenario will be discussed.

5.2 Performance of the CHE method in a shop floor scenario

In order to analyse the performance of the CHE method a dynamic simulation model (similar to [4]) is used. This scenario comprises a shop floor with 3×3 machines and 3 different job types. Every job enters the system at a source and has to pass 3 production stages on its route to the sink. These production stages comprise 3 parallel lines of machines, which are able to process every job type with different processing times (Table 1).

Type /Line	Line 1	Line 2	Line 3
Type A	2:00	3:00	2:30
Type B	2:30	2:00	3:00
Type C	3:00	2:30	2:00

Table 1: Processing times of different lines [h:mm]

The arrival rate of the jobs is set to sine function (4) to model demand fluctuation during the simulation period of 30 days with a mean arrival rate of λ_m=0.4 1/h.

$$\lambda\ t\ = \lambda_m + \alpha \cdot \sin(t) \tag{4}$$

The amplitude α determines the intensity of demand fluctuations. It is set to 0.2 1/h. Before processing, each part has to be assigned to a production line. Therefore the CHE is used for autonomous decision-making. To pursue a reduction of TPT, the attractant is modelled as the workload of each machine and its corresponding buffer.

The simulation results presented in Figure 5 show the performance of this method concerning different values of *k*. Again to reduce statistical effects each simulation runs is conducted 10^3 times. Figure 5 presents the mean TPT of simulation runs for certain *k* values. It can be noticed, that the parameter *k* influences the dynamic behaviour of this system. Interestingly the lowest mean TPT can be found for *k*=0.03 which apparently contrasts Figure 4. According to Figure 4 one can expect that more parts choose the machine with the lowest workload for bigger *k* values.

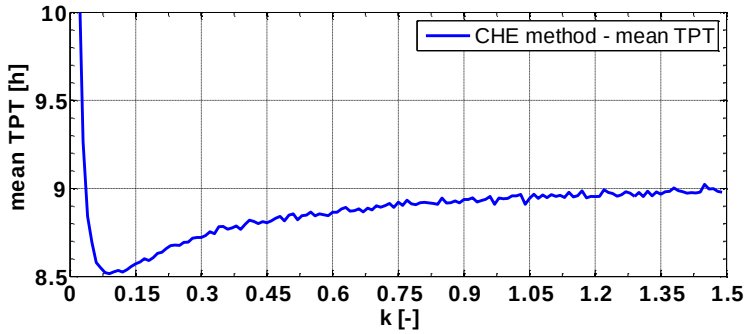

Figure 5: Mean TPT of 3x3 machines scenario for varying *k*

In contrast to this expectation Figure 5 shows that a certain amount of suboptimal decisions, which is implied by a smaller *k* value, improves the performance of the total system. On the other hand too small values of *k* lead to a sudden increase of the mean TPT. This indicates that the decisions of single parts are not adequate below this point (*k*=0.03).

6 SUMMARY AND OUTLOOK

This paper presented a bio-inspired autonomous control method, based on bacterial chemotaxis and its implementation to an algorithm. It was shown, that autonomous decisions made by this method are mainly influenced by the parameter of the tumbling probability *k* and the corresponding gradient *g*. Variations of the parameter *k* change the decision quality of single objects, as well as the dynamic behaviour of the total system. Interestingly the total system performs better in case of a soft tumbling probability (*k*<0.09), which contrasts the targets of single parts. Thus parameter *k* can be used to adjust of the systems performance. Dynamic adaptations of this parameter may also be promising and will be

investigated in the future. Furthermore exploration of different system variables, e.g. set up times, disturbances or a bigger machine environment, is necessary to provide a profound evaluation of this novel method.

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