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Using genetic programming and simulation to learn how to dynamically adapt the number of cards in reactive pull systems

7 Q1 Lorena Silva Belisário^{*}, Henri Pierreval

8 Clermont University, LIMOS UMR CNRS 6158, IFMA, Campus des Cézeaux, CS20265, F-63175 Aubière, France

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ABSTRACT

Pull control systems are now widely used in many types of production systems. For those based on cards, 23 determining their number is an important issue. When the system is submitted to changes in supply and 24 demand, several researchers have demonstrated the benefits of changing this number dynamically. 25 Defining when and how to do so is known as a difficult problem, especially when such modifications 26 in customer demands are unpredictable and the system behavior is stochastic. This paper proposes a Sim- 27 ulation-based Genetic Programming approach to learn how to decide, i.e., to generate a decision logic that 28 specifies under which circumstances it is worth modifying the number of cards. It aims at eliciting the 29 underlying knowledge through a decision tree that uses the current system state as input and returns 30 the suggested modifications of the number of cards as output. Contrarily to the few learning approaches 31 presented in the literature, no training set is used, which represents a major advantage when real-time 32 decisions have to be learnt. An adaptive ConWIP system, taken from the literature, is used to illustrate the relevance of our approach. The comparison made shows that it can yield better results, and generate the 34 knowledge in an autonomous way. This knowledge is expressed under the form of a decision tree that can 35 be understood and exploited by the decision maker, or by an automated on-line decision support system 36 providing a self-adaptation component to the manufacturing system. 37

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42 1. Introduction

 Pull production control systems aim at managing finished inventory and work-in-process (WIP) in order to satisfy customer demands in time while minimizing the related costs in the manu- facturing process. They are generally based on the Just-In-Time (JIT) philosophy, whose objective is to deliver the right parts, at the right time, at the right place, and in the exact amount needed. The most well-known pull systems are probably Kanban ([Lage](#page--1-0) [Junior & Godinho Filho, 2010; Monden, 1981\)](#page--1-0) and Constant WIP (ConWIP) [\(Prakash & Chin, 2014; Spearman, Woodruff, & Hopp,](#page--1-0) [1990\)](#page--1-0), where production is allowed only upon the reception of authorization cards, used to control all the manufacturing process ([Bollon, Di Mascolo, & Frein, 2004; González-R, Framinan, &](#page--1-0) [Pierreval, 2012\)](#page--1-0). The former uses a loop of cards at each stage of the process and the latter is simpler, since it considers the whole process as a single-stage system in which each part is pushed through the system as soon as its production is allowed at the input of the system by a card. These two types of system are

Corresponding author.

E-mail addresses: lorena.silva-belisario@ifma.fr (L.S. Belisário), [henri.](mailto:henri.pierreval@ifma.fr) [pierreval@ifma.fr](mailto:henri.pierreval@ifma.fr) (H. Pierreval).

<http://dx.doi.org/10.1016/j.eswa.2014.11.052> 0957-4174/© 2014 Published by Elsevier Ltd. illustrated in $Fig. 1$. One important issue of such pull control sys- 60 tems is to determine the appropriate number of cards for each 61 loop. This problem has been widely addressed using optimization 62 approaches, which aim at finding those numbers, so as to maxi- 63 mize given performance objectives (see for example [\(Paris &](#page--1-0) 64 [Pierreval, 2001\)](#page--1-0)). Unfortunately, the use of a fixed number of cards 65 implies a stable production environment [\(Framinan & Pierreval,](#page--1-0) 66 2012), which is often not the case. Indeed, today the market 67 changes and unpredictable fluctuations in demand occur. To face 68 these major difficulties, numerous studies have proposed to 69 dynamically adapt the number of cards, in order to render so- 70 called token-based pull manufacturing systems ([González-R](#page--1-0) 71 [et al., 2012\)](#page--1-0) capable to adapt themselves to new operating condi- 72 tions ([Takahashi, Morikawa, & Nakamura, 2004; Takahashi &](#page--1-0) 73 [Nakamura, 1999b\)](#page--1-0). 24

Despite the widespread literature related to this problem, the 75 development of adaptive control systems, whose purpose is to 76 change dynamically the number of cards in each loop of the sys- 77 tem, still represents a significant research challenge. Indeed, the 78 stochastic nature of pull manufacturing systems and their complex 79 dynamic behavior render the use of mathematical models to eval-
80 uate their performance not relevant if one wants to avoid restric- 81 tive assumptions. Moreover, determining when to add or remove 82

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 cards in real time is a problem that is difficult to address using optimization since the system state evolves along time often in a non-predictable manner. In such cases, decisions are frequently not taken in advance, but in real time, often using heuristic strate- gies, which can be more or less complex, and more or less depen-88 dent on the state of the system ([Coffman, 1976](#page--1-0)).

 Artificial intelligence (AI), in particular machine learning, can be very useful to extract the necessary knowledge to make efficient decisions about adding or removing cards, and to make it accessi- ble to decision makers, in view of their everyday use. Indeed, we are interested in learning rules of the following form:

If \langle conditions about the current system state \rangle ,

96 Then \langle add new cards \rangle or \langle remove cards \rangle or \langle do nothing \rangle .

 Unfortunately, learning require the use of suited training sets, which turn out to be quite difficult to obtain for real-time decisions ([Mouelhi & Pierreval, 2007](#page--1-0)). Providing examples or observations about the effect of a given decision, taken at time t, when the sys- tem is in a given state is generally extremely difficult since good or bad performances are induced by a sequence of coherent deci- sions taken at different instants of time. Moreover, the efficiency of decision sequences is generally difficult to measure on the very short term. As a consequence, one of the motivations of this research is to suggest a learning approach capable of generating decisions strategies, not requiring the use of such training sets, and that can be used for various pull control systems, without restrictive assumptions. In this respect, we propose to combine Genetic Programming (GP) and simulation, so that the knowledge needed to make efficient decisions is directly extracted from simu- lation runs. To the best of our knowledge, the joint use of these two techniques has not yet been studied in the literature to solve this kind of problem. The knowledge learnt can be implemented in the 115 pull control system to determine when changes should be made 116 and how many cards should be added or removed, or communi-117 cated to production managers who wish to improve their everyday practice.

 The rest of this article is organized as follows. Section 2 analyzes the literature on adaptive pull control systems, and emphasis is put on articles concerned with learning techniques. Section [3](#page--1-0) intro- duces our Simulation-based Genetic Programming approach. Sec- tion [4](#page--1-0) provides an example adapted from the literature on adaptive ConWIP control, to which our approach is applied, and our results are discussed. Finally, our conclusions and research directions are drawn in Section [5](#page--1-0).

127 2. Related research

128 Many articles have been devoted to the improvement of pull 129 control systems and several states of the art published [\(Akturk &](#page--1-0) 130 [Erhun, 1999; Bollon et al., 2004; Di Mascolo, Frein, & Dallery,](#page--1-0) [1996; González-R et al., 2012; Lage Junior & Godinho Filho, 2010;](#page--1-0) 131 [Prakash & Chin, 2014](#page--1-0)). In the eighties, [Monden \(1981\)](#page--1-0) underlined 132 that Kanban systems should be used only in presence of small fluc- 133 tuations. It is now well recognized that, when there are frequent 134 and wide variations in supply and demand, then it may not be effi- 135 cient to size the amount of WIP circulating through the system 136 using a constant number of cards ([Takahashi & Nakamura,](#page--1-0) 137 [1999b\)](#page--1-0). As a consequence, the question of how to design pull con- 138 trol adjustment mechanisms has been raised and addressed by 139 several researchers, who have suggested so-called flexible ([Gupta](#page--1-0) 140 [& Al-Turki, 1997\)](#page--1-0), reactive [\(Takahashi & Nakamura, 1999b\)](#page--1-0), or 141 adaptive pull control systems ([Tardif & Maaseidvaag, 2001\)](#page--1-0). Their 142 common property is to redesign the control system by adding or 143 retrieving cards, when it turns out to be relevant, so that the sys- 144 tem can remain globally efficient on a long period of time, even 145 with an unpredictable changing demand. The manner of the state of 146

Among the articles related to card controlling, a number of 147 them assume the availability of production plans or forecasts, 148 related to periods of time, which allow them to use optimization 149 methods when assigning the cards. This is for instance the case 150 of [Rees, Philipoom, Taylor, and Huang \(1987\),](#page--1-0) who developed an 151 eight-step procedure based on the statistical estimation of the 152 observed lead-time density function during the past period and 153 on demand forecasts of the next period, which they assume to be 154 obtained using standard company forecasting procedures. These 155 two types of information are used to determine the percentage of 156 the time that different numbers of cards will be needed during 157 the next period. As demand and costs are considered deterministic 158 once estimated, an analytical method is used to evaluate the differ- 159 ent possibilities. The number of cards providing the minimum 160 holding and shortage costs is selected and implemented for the 161 entire period. In such approaches, changes in the number of cards 162 are not decided in real time: they use periodic rather than dynamic 163 adjustments of cards. The contract of cards and the contract of contract of contract of contract of contract of contra

In the same vein, [Gupta and Al-Turki \(1997\)](#page--1-0) proposed a Flexible 165 Kanban System to minimize inventory and backlog. Their system is 166 initialized with a number of permanent cards and additional cards 167 can be added to compensate for the variation in processing times 168 and anticipated surge in demand, assuming that the demand is 169 known a given time in advance (equal to the duration of the plan- 170 ning period). In their simple algorithm, an analytical computation 171 of the time required to fulfill the demand, based on processing time 172 mean and standard deviation, determines the eventual increase in 173 the number of cards and the exact time to do it. The additional 174 cards are retrieved at the end of the considered planning period. 175

[Guion, El Haouzi, and Thomas \(2011\)](#page--1-0) and [Talibi, Bril El Haouzi,](#page--1-0) 176 [and Thomas \(2013\)](#page--1-0) also assume that a production plan for the 177 coming period is available. They use a heuristic based on an esti- 178 mation of the finished stock level and on replenishment delays of 179 the kanban loop to detect possible future shortages (dates and 180 missing quantities). This allows them to determine the number 181

Fig. 1. Kanban and ConWIP pull control systems.

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