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Using an agent-based neural-network computational model to improve product routing in a logistics facility

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ABSTRACT

This study tests whether a simplified neural-network computational model can make routing decisions in a logistics facility more efficiently than five 'intelligent' routing heuristics from the logistics literature. The experiment uses a real-world simulation scenario based on the Hamburg Harbor Car Terminal, a logistic site faced with managing approximately 46,500 car-routing decisions on a yearly basis. The simulation environment has been built based on a data set provided by the Terminal operator to reflect a real-world case. The simulation results show that the percent-improvement of the neural-net model's performance is 48% better than that of the best routing heuristic tested in previous studies. To test the applicability of the method with more complex logistic scenarios, we relaxed the sequence constraints for routing in a subsequent simulations study. If logistic complexity in terms of more freedom in decision-making is increased, the neural net model's percent-improvement performance of routing decisions is around three times better than the best-performing heuristic.

1. Introduction

Companies aim for short throughput times, high schedule reliability, and low costs as three central objectives in logistics-network management. These objectives contribute to the fulfillment of customer demands, planning reliability, and financial wellbeing (Yaged, 1973; Widrow et al., 1994; Nyhuis and Wiendahl, 2008; Michalewicz et al., 2010). Logistic routing options, however, have become more and more complex as the number of products, decision points, and global suppliers and customers have increased (Warnecke, 1993; Tharumarajah et al., 1996; Choi et al., 2001; Choi and Hong, 2002; Surana et al., 2005; Wycisk et al., 2008). Many logistic scenarios, however, are too large and too dynamic so that they cannot be mapped to simplistic de-complexified mathematical expressions. Instead, we apply 'rule-directed' analytical methodsdirecting the analytical process toward the best solution (Allen and Helferich, 1990; Harrington et al., 1992).

From a complexity perspective, the complexity of decision-making is measured in terms of degrees of freedom, i.e. the number of possible alternatives or options to choose from (Cramer, 1993; Gell-Mann, 1994, 2002). This calls for the direct management of decision alternatives, and especially, the reduction of the degrees of freedom embedded in a decision to keep it manageable – but without simplifying the decision processes so much such that they do not reflect the actual problem any more. In a logistics facility, inappropriate product-routing decisions caused by unmanaged complexity can have a negative reinforcing effect and cause more drastic delays in succeeding production stages. Accordingly, fulfillment of customer demands becomes increasingly problematic due to the increased risk of failing to achieve short throughput times and high schedule reliability at lowest possible cost (Gallager, 1977; Wang and Browning, 1991; Nyhuis and Wiendahl, 2008; Windt et al., 2010a).

To better manage degrees-of-freedom, we use the simplified neural network design introduced by LeBaron (2001b) in his

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computational model of a stock market. It has been successfully applied in McKelvey et al.'s (2009) model for an agent-based computational market design for 'smart-parts' logistics and therefore is a promising basis for further developments in dealing with increased degrees of freedom in logistics systems (Choi et al., 2001; Surana et al., 2005; Pathak et al., 2007; Wycisk et al., 2008). Moreover, there is a rising demand for new modeling approaches since modeling becomes ever more difficult as degrees of freedom, uncertainty, and time constraints increase (Chambers and Mount-Campbell, 2002; Iassinovski et al., 2003; Michalewicz et al., 2010). While some recent progress has been made in using simulations to improve robustness (Caridi and Sianesi, 2000; Al-Mubarak et al., 2003; Schikora and Godfrey, 2003; Köchel and Nieländer, 2005), we see little significant evidence showing how the use of computational models – whether cellular automata, genetic algorithms, or *neural network models* (NNMs) – actually improves managerial logistics decision-making in complex systems so as to speed up the flow of goods (i.e. cars in our study) while also lowering costs (Michalewicz et al. (2010), is an exception). Thus, the objective of our article is to test whether a computational model, specifically the NNM, can actually improve logistics management given increasing degrees of freedom.

We perform our test using a simulation model derived from a real-world logistics scenario because we are interested in the applicability of our approach by companies in the logistics sector. We are aware of the limitations when selecting a single, specific case for testing, such as loss of generality and comparability. However, we think that the general advantages of NNMs have been documented elsewhere, and we now want to analyze our approach in a realistic scenario. By choosing a scenario that has been used previously for the study of different control approaches (Windt et al., 2010c), we at least partially overcome the issue of limited comparability.

In Section 2 we describe our real-world case, the Hamburg Harbor Car Terminal (hereinafter 'Terminal'), a facility that receives, stores, reworks, and dispatches approximately 46,500 cars per year. The coordination effort of all activities at the Terminal represents an illustrative logistic site faced with managing moderate degrees of freedom. We describe our use of LeBaron's (2001a, 2001b) NNM in Section 3. This includes (1) describing his simplified NNM; (2) a 'baseline test' (Test 1) of how well the simulated car-flow compares to the real-world car-flow at the Terminal; (3) testing the NNM's management of routing heuristics (Tests 2 and 3); and (4) testing whether using the NNM helps better manage car-flows under conditions of increased complexity (Test 4).

In Section 4 we describe aspects of our method: (1) the Terminal facilities; (2) the data used for our analyses; (3) the current method used in the Terminal to manage car flows; (4) the five routing heuristics applied by Windt et al. (2010c); (5) our NNM approach; and finally (6) an alternative design of the simulated database so as to assess the management performance of the NNM under conditions of increased degrees of freedom. In Section 5 we describe the results for the baseline test (Test 1), the five heuristics, the comparison between the baseline model, Windt et al.'s (2010c) heuristics, and the NNM in terms of throughput times (Tests 2 and 3), and finally the comparison of all heuristics with increased degrees of freedom (Test 4). We perform all tests with simulated data, based on recorded data from the Terminal operator. A conclusion follows.

2. An example management problem: the Hamburg Car Terminal

Fig. 1 shows an aerial photograph of the Terminal. We use this Terminal as a scenario for testing whether a NNM offers any advantage over human decision-making, given a complex situation having some number of degrees of freedom. The car-flow process at the Terminal is readily described and offers an example of changing degrees of freedom. It has a flexible production sequence and a large amount of available real-world data, presents various changes and flexibilities in the car-flow process, and easily identifiable logistics objects (cars) in a spatially and organizationally defined space (Windt et al., 2010c).

For a better illustration of the processes and the car flow on the Terminal, Fig. 2 depicts it schematically: On the upper left-hand side the cars arrive at the Terminal. The majority of the incoming cars reach the Terminal via vessel. They are unloaded from the ship and stored in the Incoming Delivery parking area (**I**). Then, cars are processed through all relevant treatment stations according to their requirements before they reach the Outgoing Exit area (**O**). Available treatment stations are (1) re-fueling cars (*gasoline or diesel*); (2) *de-waxing*; (3) *car-body repair*; (4) *car wash*; (5) *paint shop; and* (6) *final inspection.* Each car enters the Terminal with a pre-defined list of orders, which can be divided into treatment and parking orders, depending on the required treatments (if any) and the duration of the stay before being sent on. If treatment is required, between one and five treatment steps are assigned to each car. The treatment steps have a specific sequence due to processing constraints; e.g., re-fueling comes first; removal of transport protection (de-waxing) needs to come before washing,

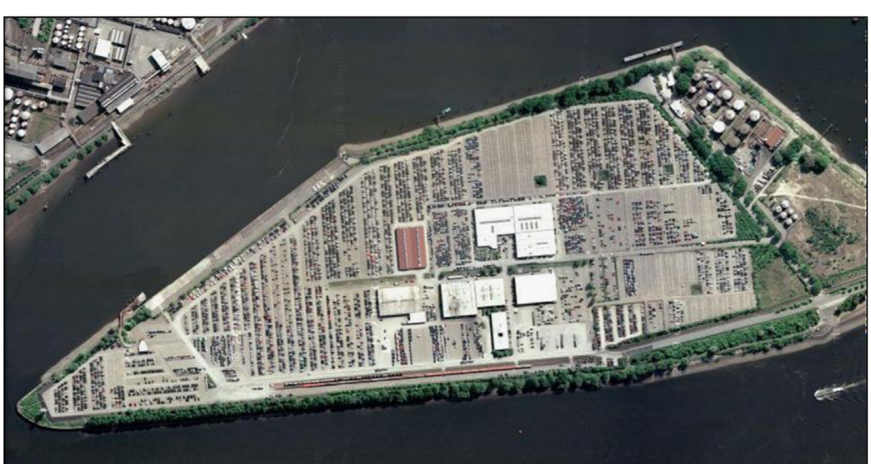

Fig. 1. Carport terminal in Hamburg harbor (Google maps, 2011_07_09).