THE ART OF APPLYING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TO CONTAINER TERMINAL OPERATIONS

FOCUSING ON AUTOMATING DECISION-MAKING

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INTRODUCTION

Which aspects of Artificial Intelligence (AI) will be most relevant to terminals in the next couple of years: natural language processing, image recognition, virtual reality, games, robots?

We believe that many AI-based benefits for container terminal operations come down to software making automated decisions, or software presenting users with recommendations on what decisions to make. We can break this topic further down into three components. First, there is the need for a proper foundation of data

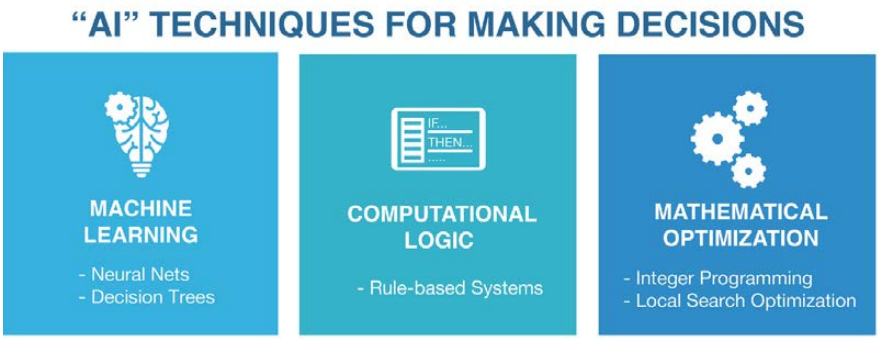

Figure 1: Garter's view on AI techniques to make automated decisions. [1]

WHAT IS MACHINE LEARNING? (FROM WIKIPEDIA)

Machine learning (ML) is the scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task.

that goes far beyond what we have today. Second, we need to be smart about the actual approach to making the decision in terms of quality and timeliness, and factoring in all the relevant data that humans take into consideration. And third, appropriate human/software interfaces are needed to present recommended decisions, confirm execution, capture priorities, and display the right information at the right time to the right user at a container terminal.

In this article, we focus on the second topic: What operational decisions are made automatically at container terminals today -- and how that will change in the future.

ARTIFICIAL INTELLIGENCE BASED AUTOMATED DECISION MAKING

In terms of automating decisions, Gartner has published three AI approaches to address the problem: optimize, computational logic, and machine learning (see Figure 1). The approaches of optimization and computational logic are great examples of how today's terminal operating software is making decisions.

Machine learning has received a lot of attention in recent years. While not new, the availability of data and advances in computing power make the technique very attractive. The most common applications for machine learning are image and video recognition, speech recognition, language translations, and personalization, used in applications such as chat bots, driverless cars, and the prioritization of web content. Also, decision-making for loan approvals and predictive maintenance are named as successful applications of machine learning [2].

The machine learning principle of self-learning based on previously recorded or generated data is intriguing, so should other decision making technologies be abandoned and be replaced by machine learning? According to Gartner [1], there is no one-size-fits-all approach. The technology should be chosen according to the nature of the decision to be made, and may include combinations of the different approaches for best results.

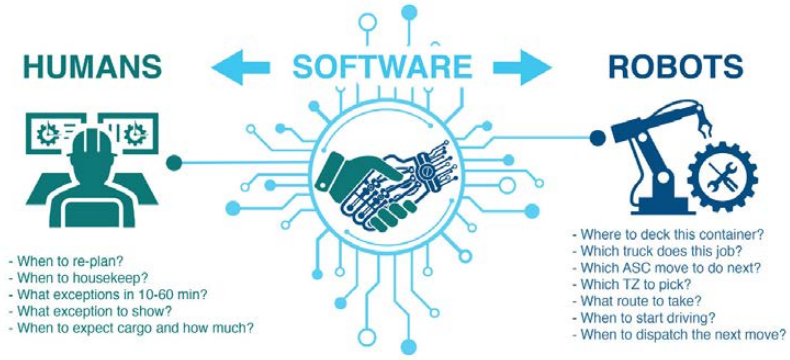

Figure 2: Software interacting with robots and humans, and example decisions the software makes.

DECISION-MAKING IN TERMINALS AND WHERE MACHINE LEARNING MAY BE A GOOD FIT

Figure 2 provides an overview of some key decisions that need to be made during vessel operations. Interestingly, many of the decisions that are made through interaction with the robots (e.g., ASCs or AGVs) are already automated today, mostly with rule-based or optimization-based approaches. On the other hand, decisions in the interaction between software and humans have received far less attention and, therefore, are less automated.

Should machine learning be used to support the automation of these decisions? Which types of decisions are closer to the applications of machine learning in other industries? Does it even matter HOW the software makes a decision, as long as it is 'good enough', and is able to respond on time, based on all the operational exceptions and changes that will always occur during vessel operations?

At Navis World in March 2019, we held a session on using machine learning at container terminals, and industry professionals contributed with their opinion and ideas. Figure 3 shows the fields of application which were picked. We chose to group them into 4 categories:

1. Recommend actions for the control room
2. Predict cargo volume, mode, timing, and cost/revenue
3. Dynamically set parameters that control the software
4. Augment existing decision-making software with insights generated through data

EXAMPLES FOR APPLYING MACHINE LEARNING TO CONTAINER TERMINAL OPERATIONS

We now briefly describe three concrete examples of applying machine learning to container terminal operations that we have worked on at Navis. These are in a different stage of development and range from stowage planning to vessel planning and vessel operations.

1. Stowage Planning

In Navis' vessel stowage solution StowMan, the module Stowage Assistant Manager semi-automatically creates plans for stowage coordinators, using a combined approach of machine learning and optimization. The optimization looks at many possible stowage solutions, assessing the quality of each while taking into account the impact of lashing forces. The exact lashing force calculation can take up to a minute and we have used machine learning to approximate this calculation. The approximation turns out to be highly accurate, as well as running about 1,000

WHY DID "IT" DO THIS?

When Google's Machine Learning based system AlphaGo played Go against the World Champion Lee Sedol, it – at times-- reportedly took quite unorthodox moves that humans found surprising and would not have taken. Still, some of these decisions were seen as key for AlphaGo to eventually win the competition. For container terminal operation, it is important to address this topic in the human / computer interaction, so that overriding automated decisions is not done too frequently as a result of humans not trusting the decisions of software. For example, we may be better off to have a waterside ASC crane wait a minute and do nothing rather than taking on a housekeeping move. In that minute, the decision-making software can gain more information about a load move that just became imminent. This phenomenon of "doing nothing" is sometimes called "deliberate idleness" to gain information in situations of uncertainty, and is a good example of a counter-intuitive decision during terminal operations.

PREDICT CARGO VOLUME, MODE, TIMING, COST/REVENUE

- Predict equipment needs
- Predict the need to prep for wind/weather
- Predict estimated time of arrival of ships, trains or trucks
- Predict mode of departure
- Predict long term yard utilization
- Suggest appointment quota per hour
- Suggest block space in yard for recurring cargo
- Predict gate visits, pickup time of imports
- Predict estimated time of departure of vessels
- Predict container damage
- Predict weight discrepancies

DYNAMICALLY SET PARAMETERS THAT CONTROL THE SOFTWARE

- Set expert decking parameters
- Update allocations
- Set prime route parameters
- Dynamic drive time calculation
- Improve EDI data accuracy
- Automate gate rule failures (including fail to deck)
- Optimize berth and crane assignment
- Set all manual input needed for automated vessel planning
- Auto create pre-defined work patterns

AUGMENT EXISTING DECISION-MAKING SOFTWARE WITH INSIGHTS GENERATED THROUGH DATA

- Optimize AGV/ASC scheduling
- Choose the right AutoStow strategy

RECOMMEND ACTIONS FOR THE CONTROL ROOM

- Predict congestions
- Manage pushrate/MaxPM
- Update CHE ranges
- Hazardous planning
- Suggest time of replanning or work queue balancing without replanning
- Understand cause and duration of crane delays and/or AGV delays
- Recommend multi-lift opportunities
- Learn how user handles exceptions and do it automatically
- Activate optimum automatic work queue activation
- Recommend times for lower energy consumption
- Suggest housekeeping/work for idle equipment

Figure 3: Functional areas that were proposed by Navis World participants to be addressed with Machine Learning.

times faster than the full calculation. We use the machine learning-based approximation during the optimization phase, and then apply the full lashing force calculation only to the final solution. With this approach, we can calculate a stowage solution of much higher quality within the time acceptable by the user stowage coordinator. Details on this application of Machine Learning have been presented at the 2018 Navis carrier and vessel solutions Conference [3].

2. Automatically Setting the Target Rate of a Work Queue

In order to fit many different types of terminal operations, N4 relies on a significant set of configuration parameters. Some terminal operations are rather static, while others should be modified on a regular basis to drive operational productivity or efficiency. Naturally, it can be inconvenient and time consuming to consistently, continuously, and accurately update such parameters, requiring highly skilled people to perform the changes. According to one global terminal operator, "You have to be superhuman to be good at this."

As an example, we studied a concrete problem of estimating the temporal duration of work queues. Container operations planned using Navis' N4 TOS are organized into work queues which group multiple container moves, and we compared the planned vs. actual work queue duration as a metric. An accurate estimate for work queue completion can help to set parameters such as target rate and better approximate the estimated time of a vessel's departure.

The analysis is based on data from operations at a container terminal of a global terminal. This dataset includes 56 vessel visits and 1,948 load and discharge work queues. We focused only on clean work queues, where the planned and executed moves were the same and there was no break of more than 10 minutes between any of the moves. With the standard calculation we found that only 39% of the work queues ended up being within a 10 minute window of their planned duration. With our machine learning approach, we were able to increase the accuracy to 78% of all work queues being within the 10 minute window.

3. Recommending Actions in the Control Room

Recommending actions in the control room is about identifying operational exceptions or problems before they occur, and once they do occur, suggesting actions on how to handle them. Most industry professionals we spoke with view this business application as high value. This is probably a good area to apply machine learning, as it is about recognizing patterns, predicting exceptions, and personalizing the content for a user or group of users – all of which are in-line with common applications of machine learning.

Navis N4 TOS today already includes a number of such predictions through simple computational logic (in Gartner's terms [1]):

- If the first move of a work queue needs to be under the quay crane in 10 minutes or less then notify the user.

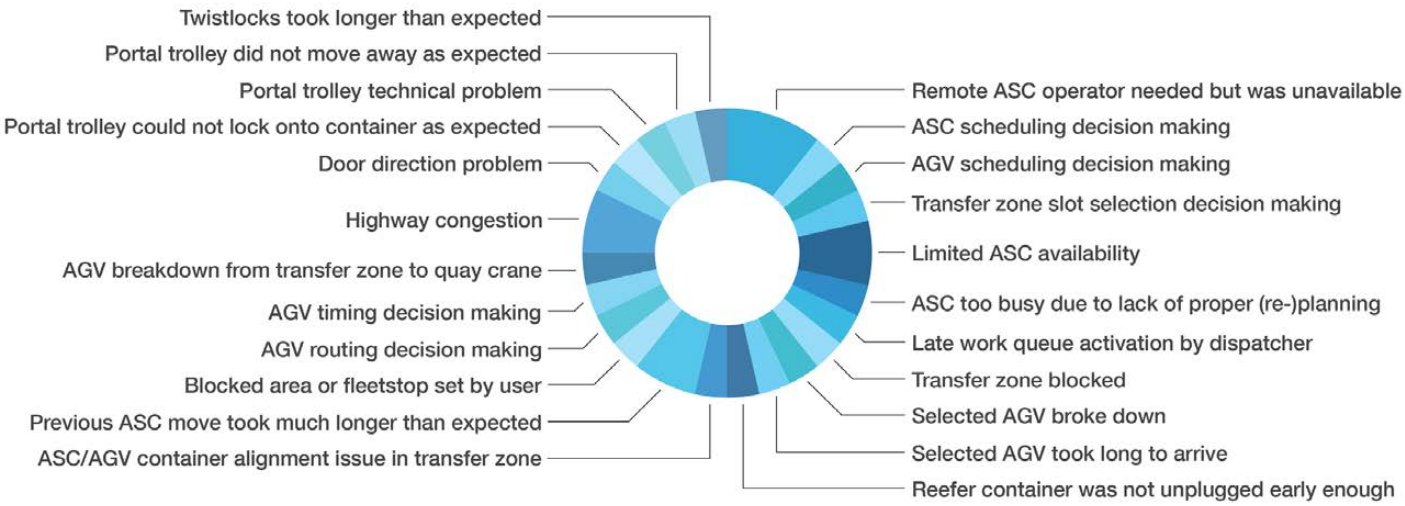

Figure 4: Example breakdown of reasons of operational delays for load moves, based on data analytics.

- If there is any move already dispatched but the previous move in the work queue is not yet dispatched, then notify the user.

We can add more of these rules to the system by manual root cause analysis of delays, which identifies less obvious (or terminal-specific) patterns. An example of such analysis is shown in Figure 4. We can have a machine learning algorithm automatically detect the patterns of delay, learn from it and derive such rules automatically. At the same time, we don't want to present too many such predictions to the dispatchers in the control room. Machine learning can help to prioritize based on the dispatcher feedback.

On the other hand, it may just be good enough to code the top 10 such rules into the decision making software and allow the user to add a few custom ones based on what they would like to see.

LESSONS LEARNED

From Navis' pre-existing work on automated decision making, and applying machine learning as a potential technique for making automated decisions in particular, we offer the following lessons learned:

- Focus on the areas with the biggest impact. Budgets are limited. Which decision to automate will yield the highest return? For example, does it make sense to tune a vessel plan to perfection if it is invalid 15 minutes later due to a broken quay crane or a delayed vessel?
- Pick the right decisions to apply machine learning. Machine learning requires many data points that need to be high quality and cleansed. If you don't have all of these or your decision can be modeled through some straight forward logic, consider keeping it simple.

Determine the meaning of the data you have. Double check whether the data actually represents what you think it represents. For example, just because a move is flagged as sequence #1 in a work queue does not mean it was the first move actually completed in that work queue.

- Bring the right set of skills together (e.g. a data scientist, data analyst, data architect, terminal operations specialist and project manager experienced in data analytics and automated decision making projects). Navis and Cargotec can bring all these skills to your project, based on Navis' experience with BI and operations monitoring platforms and comprehensive data analysis at our automated terminals, supported by Cargotec's dedicated data science team.

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ABOUT THE AUTHOR

Frederik Stork is the Sr. Director of Navis' Global Optimization and Analytics Services. Frederik's team focuses on increasing container terminal productivity and efficiency. This includes the implementation of Navis optimization and analytics software solutions along with the improvement of associated business processes. It also includes applying machine learning and related techniques to terminal data to gain insights and drive better decision making. Prior to joining Navis, Frederik was part of IBMs Software Services team in the US, where he held various consulting leadership roles. Before that, Frederik worked for ILOG, the leader in optimization software. While at ILOG, Frederik led consulting teams in the US and Germany with a focus on Supply Chain Optimization and Logistics. Frederik received a PhD in Operations Research from Berlin University of Technology.

ABOUT THE ORGANIZATION

Navis understands that as operational procsesses become more complex, efficiency, collaboration and productivity are essential. As a trusted technology partner, Navis offers the tools and personnel necessary to meet the requirements of a new and ever-evolving, global supply chain. The Navis N4 terminal operating system is a platform that can integrate partner technologies, enabling terminals to optimise productivity and enhance the service delivered to its customers.

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