Collaborative Neuro-BDI Agents in Container Terminals

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Abstract

Berth scheduling and monitoring of the vessel operations are of paramount importance in order to assure faster turnaround time and high productivity of any container terminal. The need for an intelligent system that dynamically adapts to the changing environment is apparent, as there are a limited number of berths and resources available in container terminals for delivering services to vessels. In this paper we discuss how BDI (Beliefs, Desires and Intentions) agents can be supported with Neural Network and fuzzy logic in a collaborative environment of a multi agents system for the scheduling and monitoring of vessel berths in container ports. Straightforward plans are handled by the generic BDI architecture. Complex planning which requires the learning and adaptability behavior is modeled with neural networks. Beliefs with fuzzy scenarios are modeled with fuzzy logic enabling agents to make rational decisions in the environment of uncertainty. Agents can autonomously adapt to the changing environment in assigning berths for vessels.

1. Introduction

Shipping, one of the World's largest industries, consists of sectors and each sector is approaching the IT revolution in different ways for the achievement of competitive advantages over competitors.

Agent based systems based on practical reasoning system, which perhaps use philosophical model of human reasoning have been used in achieving optimal solutions for many business application in the recent past. A number of different approaches have emerged as candidates for the study of agent-oriented systems [Bratman et al., 1988; Doyle 1992; Rao and Georgeff, 1991c; Rosenschein and Kaelbling, 1968; Shoham 1993]. The architecture has been implemented using PRS, JAM, dMAS and JACK and demonstrated the usability in number of business systems[7].

Neuro-BDI architecture used in SCHEDULE-AGENT and fuzzy logic in BERTH-AGENTS in the scheduling of vessels are described in the paper. Neural network training and fuzzy rules used in the Neuro-BDI agent architecture is not fully described in the paper due to limitations of space. The research is carried out at the School of Business Systems, Monash University, Australia, in collaboration with the Jaya Container Terminal at the port of Colombo, Sri Lanka.

The rest of the paper is organized as follows: Section 2 provides an introduction to berthing system and the generic parameters required in allocating a berth for a vessel. Section 3 describes the proposed Neuro-BDI architecture for the agents in a container terminal. Section 4 describes a test case scenario. Future work and conclusions are provided in Section 5.

2. Generic Berthing Systems of a Container Terminal

In current operations, shipping line will inform the respective port the Expected Time of Arrival (ETA) three months before the arrival of the ship. The shipping line then updates the port daily about any changes to the original plan of arrival of the vessel. Arrival Declaration sent by shipping lines to Ports generally contains the Date of arrival, Expected Time of Arrival, Vessel details, Number of containers to be discharged, Number of containers to be loaded, any remarks such as Cargo type, Berthing and Sailing draft requirements, Crane outreach required, Air draft, etc.

3. Neuro BDI Agent Architecture

We have designed a group of multi agents for the Vessel berthing and scheduling of a container terminal. Agents inherits the architecture of BDI concept initially and a trained neural networks and fuzzy logic have been implemented in finding an optimum solution in the scheduling and monitoring process of the system

Tasks involving berths, vessels and scheduling are being proposed to handle by three different types of agents namely, VESSEL-AGENT, SCHEDULING-AGENT and BERTH-AGENT. Each agent handles the set

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of tasks depending upon the knowledge they have and essentially communicate and co-operate with other agents in attaining the final desires of the system. A set of hierarchical levels in the plans is proposed in finally achieving desires of the agents assuring collaborative effects in the whole architecture. Agents have their own set of beliefs in their internal structure and another set of beliefs are defined as global where all the different agents can access these global sets of beliefs. Main agents in the system are shown in figure 1.

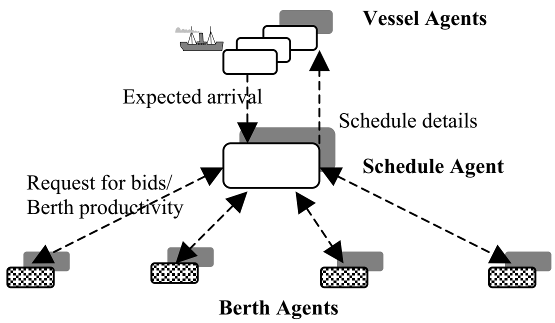

Figure 1. Main agents in the proposed system

SCHEDULE-AGENT in the proposed Neuro-BDI architecture is deployed to handle mainly the vessel berthing, rescheduling and shifting tasks in the terminal. VESSEL-AGENT is responsible in the declaration of vessel details to the terminal. BERTH-AGENT handles the berth related tasks such as resource allocations, compute gross crane productivity etc. Functionalities of the SCHEDULE-AGENT and the BERTH-AGENT are described as follows.

3.1. The SCHEDULE AGENT

The main components of the SCHEDULE-AGENT are EVENT-HANDLER, PLAN-SELECTOR, PLAN-MONITOR, STATIC-FILTER, IMPACT-ANALYZER, NEGOTIATOR and BERTH-ASSIGNER. The different components and the proposed Neuro-BDI architecture for SCHEDULE AGENT are shown in figure 2.

3.1.1. The EVENT-HANDLER Component

EVENT-HANDLER selects the list of events from the event queue based on the priority factors defined. Some of the events identified by the EVENT-HANDLER are Vessel-declaration( ), Gross-crane-productivity( )

3.1.2. PLAN-SELECTOR Component

PLAN-SELECTOR fires when an EVENT-HANDLER is sent messages indicating the events to be handled in the system, which require execution. Selected plans called intentions show the various paths to be executed in achieving desires of the system. In the dynamic nature of the application system, sometimes, initial plans set may have to be modified due to the dynamic change of the environment.

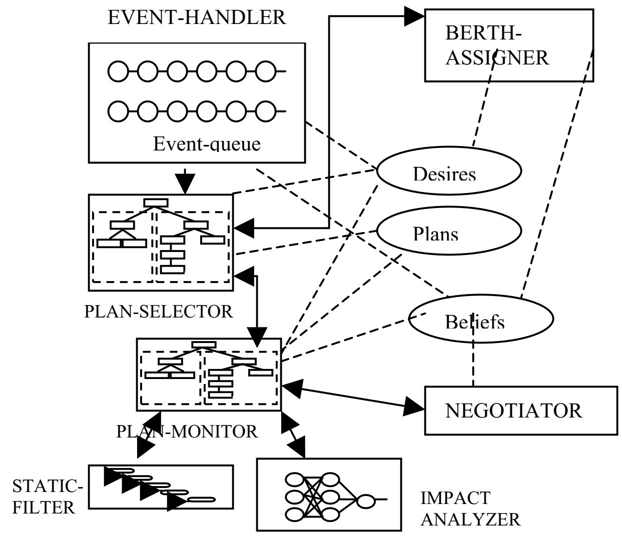

Figure 2. Neuro-BDI architecture for Schedule-Agent

Plan is identified by Plan-name(ET,PC,BD,ST) in our system as shown in figure 3.

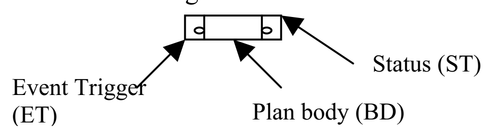

Figure 3. Structure of a plan

Where ET : Event trigger, PC : Pre conditions required for the execution of the plan, BD : body of the plan explaining steps in the plan, ST : status of the outcome of the plan

3.1.3. PLAN-MONITOR Component

PLAN-MONITOR component is deployed to receive a set of plans passed by the PLAN-SELECTOR and decides what set of initial plans to be executed and what are the remaining plans required to defer without executing. This would enable agents to initially achieve sub goals with the set of initial plans and observe the environmental changes affects beliefs during the execution of the first set of plans. PLAN-MONITOR instructs BASIC-FILTER to execute the set of initial plans identified. During this initial execution of the plans some of the beliefs would have dynamically changed and therefore the next level of DYNAMIC-FILTERING is carried out in accommodating dynamic behavior of the scheduling process.

3.1.4. STATIC-FILTER Component

STATIC-FILTER component executes the basic plans set by the PLAN-MONITOR. Few static plans identified for vessel-schedule( ) are

: check-outreach-of cranes( )
: Sailing-draft-requirement( )
: Berthing-draft-requirement( )
: Berth-gap( )
: Filtering-berths( )
: Compare-time( )

Agent beliefs are updated with the results of the sub goal of Static-filtering-of-berths( ). The PLAN-MONITOR component will be informed with the filtered berths. Filtered berths from the sub-goal are considered by the PLAN-MONITOR for the next level of plan.

3.1.5. IMPACT-ANALYZER Component

IMPACT-ANALYZER component is a trained neural network with backpropagation, which has the capability to execute the next levels of the plans called intentions set by the PLAN-MONITOR. A set of new beliefs from the BASIC-FILTER and other dynamic changes as beliefs from various selected BERTH-AGENTS are fed in to the trained neural network for predicting the expected Time for the operations(EOT_i) and ESD_i.

NOB_i, Yard location of the boxes, Number of trucks, TSO, LEV, LEB, WET and Cargo type are used as input neurons to predict EOT_i, and ESD_i for berths. Autonomy of the SCHEDULE-AGENT behavior is shown as they dynamically decide the possible berth-agents to be contacted for next level of plans. BIRTH-AGENTS then send their expected GCP, which is also used as a input in predicting EOT_i and EDS_i for each berth as shown in figure 4

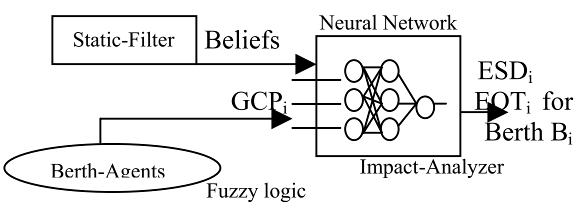

Figure 4. Beliefs on Impact-analyzer

3.1.6. The NEGOTIATOR Component

The NEGOTIATOR component evaluates the sub goals reached and plans for the negotiations with Berth-agents and vessel-agents for the optimum scheduling of berths.

3.1.7. The BERTH-ASSIGNER Component

BERTH-ASSIGNER component finally assigns the berths for vessels giving details such as Berth name, ETB, ETC ETS, Expected GBP of the berth etc.

3.2. The BERTH-AGENT

With respect to the request of bids from the SCHEDULE-AGENT to compute the expected GCP for new vessels, the BERTH-AGENTS uses fuzzy inference rules in the Impact-analyzer component of the BERTH-AGENT. Linguistic variables and the values used by the BERTH-AGENTS for the computation of GBP are : Crane productivity of Berth $B_i = CPR_i$ {VP,P,M,A,G, VG}, No of cranes available in berth B_i=NOC_i{P,A,G and VG}, Operator competence in the berth B_i=OPS_i{VP,P,M, A, G and VG} and linguistic output of GCP_i of berth B_i={VP,P,A,G,VG,EX}. Where, VP-very poor, P-poor, M-marginal, A-average, G-good, VG-very good, EX-excellent

4. A Test Case Scenario

In this section we describe a test case scenario of a scheduling a vessel using Neuro-BDI agent model. Table 1. Shows the vessels at berths at time T_i

Vessel-agent sends an event which contains minimally vessel-name-“Kota”, ETA-“St0315”, NOB-“849”, VBD-“11.5m”, VSD-“12m”, CTR-“Normal”, VCR-“13m”,. Even though all four berths satisfy berth draft, crane outreach, distance between vessels, requirements for serving the vessel ”Kota”, only two berths, JCT2 and JCT3 have been selected as $|ETC_i - ETA| <= l$, where l is the time factor. Current beliefs are then updated and control is passed to the IMPACT-ANALYZER component. Autonomy of the SCHEDULE-AGENT is shown here as it requests only selected berth-agents to bid their expected GCP for the new vessel” Kota”.

Table 1. Vessels at berths

	Vessels at the Terminal, time T_i			
Beliefs	Maersk	ZIM	APL	Jammi
CTY	Normal	Normal	Normal	Normal
NOB	550	525	750	490
VSR	12m	12m	14m	12m
VCR	13m	13m	18m	13m
Berth	JCT1	JCT2	JCT3	JCT4
BDR	12m	12m	14m	14m
COR	13m	13m	18m	18m
NOC	3	3	4	2
ETC	St1220	St0300	St0435	St1530

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BERTH-AGENTS then compute the GCP using linguistic fuzzy inputs CPR, NOC and OPS. Where crane productivity(CPR) of crane C_i is=(No-of-moves/Total hours). BERTH-AGENTS then send their bids as GCP_{jct2}=40 and GCP_{jct3}=90 back to the SCHEDULE-AGENT. Then plan-monitor executes next set of plans only for berth JCT2 and JCT3. Current set of beliefs and GCP of the above two berths are sent to trained neural network for prediction of expected time required at individual berths for the completion of the operations. Then these $GCP_{i..}$ NOB_i, location of boxes, no of trucks, LEV,LEB, WET and cargo type for berth JCT1 and JCT2 are sent by the plan-monitor to the IMPACT-ANALYZER to get the EOT and ESD for the above berths.

EOT_{jct2}=21.25hrs, ESD_{jct2}=2.25hrs and EOT_{jct3}=9.43hrs , ESD_{jct3}=2.40hrs are sent by the IMPACT-ANALYZER and control is passed to the NEGOTIATOR component. Reactive behavior of the schedule-agent is shown here as the negotiator component reacts to the receipt of above EOT for berths. Negotiator requests to improve the EOT_{jct2} as $|EOT_{jct2} - EOT_{jct3}| >= k$ where k is the negotiation factor. ETC of berth JCT2 is earlier than the ETC of berth JCT3, but berth JCT3 has been assigned for the vessel" Kota" as it shows higher productivity and finally assures earlier ETC for the vessel "Kota".

5. Conclusions and Future work

Introduction of Neural networks in the Schedule-agent have shown tremendous improvement in making decisions with dynamically changing beliefs in the environment. It is virtually impossible to compute the expected time of completion for a particular vessel as many factors have positive and negative impacts on the operations in a berth. These aspects are effectively handled in the trained neural network that resides in the SCHEDULE-AGENT assuring better realistic predictions of required operation time. Limitations in learning and understanding the social scenarios that affects the operations in vessel scheduling have minimized in the proposed Neuro-BDI agent architecture in our research work.

Use of fuzzy theory has again shown improved decision making capabilities in the BERTH-AGENTS in bidding gross crane productivity of individual berths. Selection factors used in the negotiator-component would help to dynamically adjust the plans that were originally set.

Finally, we propose to expand the research work to introduce learning behaviors embedded in beliefs and plans. Autonomous plans then would help in recognizing partially defined information or beliefs, where uncertainty prevails. Agents should be able to specify a set of possible avenues in successfully completing a desire justifying the intentions structures before its execution. Plans guided by the learning behaviors of the agents should also indicate alternate plans if failed during the execution.

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