BDI AGENTS WITH FUZZY ASSOCIATIVE MEMORY FOR VESSEL BERTHING IN CONTAINER PORTS

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Abstract: Faster turnaround time of the vessels in berths has direct impact on the improvement of terminals productivity. The need for an intelligent system that dynamically adapts to the changing environment is apparent, as there is limited number of berths and resources available in container terminals for delivering services to vessels. BDI (Beliefs, Desires and Intentions) agents are being proposed in a complex collaborative environment in the vessel scheduling assuring better management and control in the terminal. BDI agents to deal with many criteria and different goals with uncertain beliefs, it is proposed that fuzzy associative memory to use in the planning process of the BDI architecture facilitating better decision making in the whole process. In this paper we propose hybrid BDI architecture with fuzzy associative memory in handling uncertainty issues of the vessel berthing in container terminals. Execution of Plans in a collaborative multi agent environment would be strengthened with the introduction of fuzzy associative memory in BDI agents.

1 INTRODUCTION

Berthing system of a container terminal requires to determine expected berthing time (ETB), expected completion time (ECT) of the vessels, a birth, allocation of cranes, labour, trucks for the stevedoring (loading and discharging) of containers assuring maximum utilization of resources and finally guaranteeing the high productivity of the terminal.

Agent oriented systems are 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 (Winikoff, 2001) has been implemented and demonstrated the usability in number of business systems.

BDI agent model is probably the most mature of the intelligent agent models and has been adopted by a few industrial applications. Berthing system in container ports will have to satisfy various constraints to a certain degree in making rational decisions. In the work described, multi agent systems model in container terminals have been extended with the fuzzy associative memory which greatly useful in handling uncertainty and vagueness in the scheduling of vessels. In this paper, we describe Hybrid BDI agent architecture coupled with fuzzy associative memory in berth scheduling for vessels in a container terminal.

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 in container terminals. Section 3 describes the background of the BDI agent model. Section 4 describes the proposed hybrid BDI architecture for the agents in a container terminal. Section 5 describes the schedule agent.

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Section 6 describes a test case scenario. Future work and conclusions are provided in Section 7.

2 VESSEL BERTHING SYSTEM IN 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.

Use of conventional software techniques to solve this type of problems would cost very much for the implementation and difficult to do so as intelligence is required in managing the dynamic behavior of such systems. Berthing system of a container terminal is responsible for computing Expected time of berth(ETB), Expected time of completion (ETC), Expected sailing time (EST), allocation of a berth, allocation of resources such as Cranes, Trucks, labor etc.

3 BDI AGENTS

In the AI community the beliefs-desires-intention (BDI) model has become to be possibly the best-known and best-studied model(Georgeff, 1998) of practical reasoning agents. Beliefs mean the information about environment and can be modelled as database records. Desires are the objectives to be achieved by the agents. These may have different parameters to set the priority of achieving the objectives of the agent. Intentions are the current selected plans for the execution Plans are used to achieve future desires or states in the problem domain. Agent considers many options in finally achieving the goal set for the problem domain.

The first point to note regarding the execution cycle given below will not observe dynamically changing world during the execution of first set of plans. In our Proposed hybrid BDI model for the vessel berthing, different levels of plans are being identified in achieving the final goals. BDI execution cycle is given below:

Initialise-state ();
Repeat
Options:=option-generated(event-queue);
Selected-options:=deliberate(options);
Update-intentions (selected-options);
Execute ();
Get-new-external-events ();
Drop-successful-attitudes ();
Drop-impossible-attitudes ();
End repeat

4 HYBRID BDI AGENTS

Tasks involving in berths, vessels and scheduling are being proposed to handle by three different types of agents namely, VESSEL-AGENT(VA), SCHEDULING-AGENT(SA) and BERTH-AGENT(BA). Each agent handles the set 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. VA is primarily responsible for informing the vessel details to other agents. SA schedules the vessels and BA is responsible in assuring faster turnaround of vessels. Main agents in the system are shown in figure 1.

Basic control loop of the BDI is refined in facilitating agents to capture the vessel berthing environmental changes and allow replanning (Wooldridge, 2000) during various stages. Refined BDI execution cycle is shown below:

$B := B_{init}$; /* initial beliefs*/
$I := I_{init}$; /* initial intentions */
While True do
get next percept p;
$B :=$ Update(B_{old} ,p); /* update beliefs */
D := deliberate- options(B,I);
I := filter-options(B,D,I);
π := plan(B,I) /* choose plans */
while not empty (π) do
α := head(π); /* initial set of plans*/
execute(α);
π := tail(π); /* next set of plans */
get next percept p; /* observe beliefs */
$B :=$ Update(B_{old} ,p); /* update beliefs */
If not sound(π, I, B) then
π := plan(B,I); /* allow replan */
end-if
end-while
end-while

Where, B indicates the beliefs and B_{old} means earlier beliefs, D for desires and I for intentions. A percept p is an input from the environment. Set of of possible desires for the current beliefs and intentions are being selected from the *deliberate-option ( )* function. Then agent chooses between competing alternatives, and commits to achieve them is given in function *filter-options(*) function. These chosen options then become intentions *I*. Function *sound(π, I, B)* allows agent to determine whether its earlier plan is still appropriate in order to achieve the current intention, if not, then it engages in further reasoning to find an alternative plan. This implies some (Wooldridge, 2000) degree of reactivity.

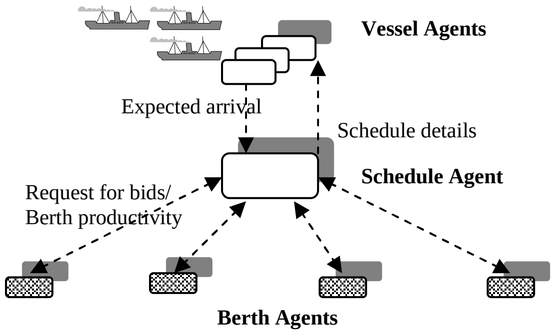

Figure 1: Main Agents in the proposed vessel berthing system

Use of fuzzy associative memory in the BDI agent model is described in the next section.

4.1 Fuzzy Associative Memory

Vessel scheduling in a container terminal is very complex. This is mainly because, there are several tasks to be executed together, uncertainty and vagueness of the data, objectives are prioritised, some objectives are partially satisfied etc. As with many real life decision-making situations, it is usually not possible to fulfil all objectives perfectly when building berth schedules. Fuzzy associative memory used in the BDI model essentially helps to minimize the above constraint in vessel scheduling.

Consider the classical set *A* of the universe *U*. A fuzzy set *A* is defined by a set or ordered pairs, a binary relation,

$$A = \{(x, \mu_A(x)) \mid x \in A, \mu_A(x) \in [0,1]\}, \quad (1)$$

Where $\mu_A(x)$ is a function called *membership function;* $\mu_A(x)$ specifies the grade or degree to which element x in *A* belongs to the fuzzy set *A*. Definition (1) associates with each element x in *A* a real number $\mu_A(x)$ in the interval [0,1] which is assigned to x. Large values of $\mu_A(x)$ indicate higher degree of membership. A fuzzy rule can be defined as a conditional statement in the form :

R1 : IF x is A
AND y is B
THEN z is C;

where x, y, z are linguistic variables; and A,B,C are linguistic values determined by fuzzy sets on the universe of discourses X and Y, respectively.

The proposed agent model use Mamdani fuzzy associative memory in the schedule-agent (BDI) of container terminal is described in the following section.

5 THE SCHEDULE AGENT

Vessel scheduling tasks are being carried out by the various components in the schedule-agent(SA). Steps shown in the refined BDI execution cycle is being followed by the agent, further SA uses fuzzy associative memory when there are instances of data uncertainty. 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.

Events are extracted from percept in EVENT-HANDLER component and subsequently agent's beliefs are updated. VA may send ETA, NOB, and LEN etc of a new vessel to SA. This triggers SA to compute ETB for the new vessel.

Deliberation process in the PLAN-SELECTOR component chooses intentions in achieving a desire. Set of plans is then identified by the PLAN-SELECTOR for execution. For e.g. SA may have plans to check the berthing/sailing draft requirements, and crane outreach requirements of the berths.

PLAN-MONITOR component monitors the execution of committed plans by the agent. if PLAN-MONITOR ever determines that its next level plan is no longer appropriate in order to achieve the current intentions, then it finds an alternative plan.

STATIC-FILTER will execute the initial set of plans in finding out the suitable berths. IMPACT-ANALYZER uses fuzzy associative memory in

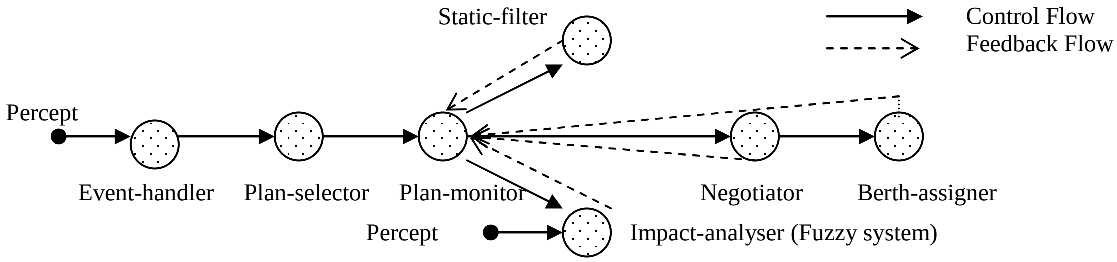

Figure 2: Components of the Schedule-agent

selecting the most efficient berth from the earlier selected berths for the cargo operations of the new vessel. Negotiations required to improve the berth productivity given by BA's will be handled by the NEGOTIATOR component. Final berth schedule indicating the ETB for new vessels is being assigned by the BERTH-ASSIGNER component in the SA. Next section describes the use of fuzzy associative memory in IMPACT-ANALYSER component for the selection of a suitable berth for the new vessel.

6 THE IMPACT ANALYSER COMPONENT WITH FUZZY ASSOCIATIVE MEMORY

The primary objective of the IMPACT-ANALYSER is to find out a berth, which can commit the highest productivity in serving the new vessel. Firstly, BA requests to send the average berth productivity (GBP_i) that individual berths can commit for the cargo operation of the new vessel. GBP of a berth *i* is given as,

$$GBP_i = \frac{1}{N} \sum_{N=1}^{N} GCP_i$$

Where, N is number of cranes used in the berth and the gross crane productivity(GCP_i) indicates the number of moves per hour by crane *i*.

Operational delays (ODL_i) in various berths are considered at this point as it has a direct impact on the completion of cargo operations in a berth. Number of trucks (NOT_i^{vessel}) that can be assigned for the loading and discharge of the boxes in each berth is also considered at this point by the SA. The above fuzzy input parameters GBP_i, ODL_i and NOT^{vessel} are considered in computing the expected vessel productivity (EVP_i^{vessel}) of the new vessel. Time required for the completion of cargo operations (EOT_i^{vessel}) of a new vessel in berth *i* is then calculated.

Impact-analyser component uses three linguistic input variables GBP_i , NOT^{vessel} and ODL_i to compute expected vessel productivity in berth *i* for the new vessel, EVP_i^{vessel}. The ranges of the linguistic variables are defined and triangle and trapezoid shapes are used to represent the fuzzy sets in the proposed system. Mamdani fuzzy inference system used by the IMPACT-ANALYSER component is shown in Figure 3.

Linguistic values for the variables and their notations used are described below:

GBP_i = *{Very-Low, Low, Rather-Low, Average, Rather good, Good, Very Good}*

NOT^{vessel} = *{Very-Few, Few, Rather-Few, Average, Rather-Large, Large, Very-Large}*

ODL_i = *{Small, Average, Big}*

Linguistic values identified for the output variable EVP_i^{vessel} in the fuzzy associative memory are as follows:

EVP_i^{vessel} = *{Very-Low, Low, Rather Low, Average, Rather-High, High, Very-High}*

The knowledge based was implemented with 147 fuzzy rules. Linguistic variables and their ranges used in the fuzzy associative memory are shown in the following tables.

Table 1: Linguistic Variable: GBP_i

Value	Notation	Range
Very Low	*VL*	*[0 –20]*
Low	*L*	*[15-35]*
Rather-Low	*RL*	*[28-45]*
Average	*A*	*[38-50]*
Rather-Good	*RG*	*[40-60]*
Good	*G*	*[55-85]*
Very good	*VG*	*[75-115]*

Table 2: Linguistic Variable: NOT^{vessel}

Value	Notation	Range
Very-Few	*VF*	*[0 –3]*
Few	*F*	*[2-5]*
Rather-Few	*RF*	*[3-6]*
Average	*A*	*[4-7]*
Rather-Large	*RL*	*[6-9]*
Large	*L*	*[8-12]*
Very Large	*VL*	*[11-15]*

Table 3: Linguistic Variable: ODL_i

Value	Notation	Range
Small	*S*	*[0-5]*
Average	*A*	*[3-8]*
Big	*B*	*[7-15]*

Table 4: Linguistic Variable: EVP_i^{vessel}

Value	Notation	Range
Very-Low	*VL*	*[0-15]*
Low	*L*	*[12-30]*
Rather-Lowl	*RL*	*[25-40]*
Average	*A*	*[35-50]*
Rather-High	*RH*	*[42-65]*
High	*H*	*[56-90]*
Very-High	*VH*	*[72-110]*

A sample test case scenario in a container terminal is described in the next section.

6 A TEST CASE FOR VESSEL BERTHING

A berthing situation at Jaya container terminal (JCT), port of Colombo has been simulated with BDI agents and fuzzy associative memory in BA. JCT has four main berths: *JCT1, JCT2, JCT3 and, JCT4.* Table 5 shows the berth occupancies at a given point of time in JCT.

Table 5: Berth Occupancy in JCT

	Vessels at the Terminal, time T_i			
Beliefs	*Maersk*	*ZIM*	*APL*	*United_V*
NOB	550	525	750	490
VCR	13m	13m	18m	13m
Berth	*JCT1*	*JCT2*	*JCT3*	*JCT4*
COR	13m	18m	18m	18m
ETC	Sat1220	Sat0300	Sat0435	Sat0500

Declaration of a new vessel *ZIM-JAPAN (ZIMJ)* has been sent by VA for scheduling. Declaration of vessel *ZIMJ* minimally contains: ETA_{zimj} = Sat0315, NOB_{zimj} = 1650, VCR_{zimj} = 18m, etc.

Table 6 shows the inputs and final output of expected vessel productivity (EVP_i^{vessel}) of individual berths. IMPACT-ANALYSER of the SA will use the fuzzy based expert knowledge in computing the EVP_i^{vessel} of individual berths. Figure 4a, 4b and 4c show the decision surfaces produced for the rule base learnt by the agent.

Table 6: Sample inputs and output value

	GBP	ODL	NOT	EVP^{vessel}
JCT2	62	5	4	37.7
JCT3	80	6	5	48.3
JCT4	99	5	3	64

Outputs of the EVP_i^{vessel} received from the Fuzzy inference system will be used to compute the expected time required for the completion of cargo operations (EOT_i^{vessel}) of the new vessel *ZIMJ* in the above berths. Following equation is used to compute the EOT_i^{vessel} .

$$EOT_i^{vessel} = \frac{NOB^{vessel}}{EVP_i^{vessel}}$$

With above information, BERTH-ASSIGNER will assign a berth, which indicates the minimum EOT for the new vessel.

7 CONCLUSIONS AND FUTURE WORK

Paper discussed the use of BDI agents in a complex multi agent environment in the shipping industry. Main BDI execution cycle is refined enabling agents to replan or to select alternative plans in achieving its original desires or intentions. This would essentially enhance the agent's ability in assigning berths for vessels in container terminals

Paper also outlined the use of fuzzy associative memory in BDI agents, especially in dealing with vague and uncertainty situations in the planning stage of the vessel berthing system.

We plan to extend the research work to incorporate fuzzy expert knowledge into the BDI architecture, which would provide necessary infrastructure for BDI agents to reconsider its intentions dynamically.

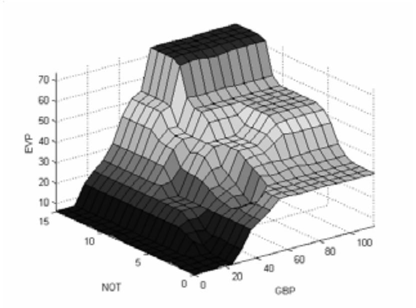

Figure 4a: Decision surface for GBP and NOT

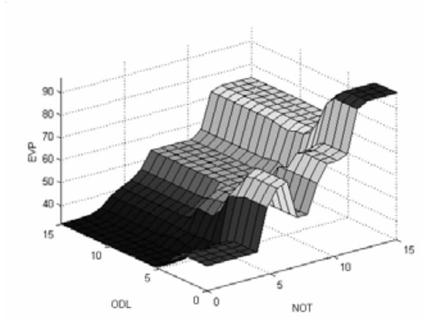

Figure 4b: Decision surface for NOT and ODL

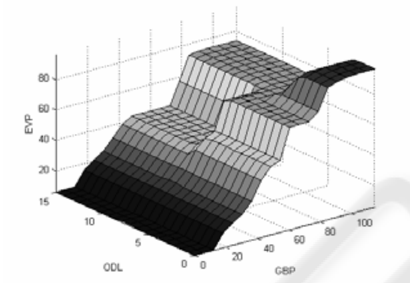

Figure 4c: Decision surface for GBP and ODL

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