HANDLING MULTIPLE EVENTS IN HYBRID BDI AGENTS WITH REINFORCEMENT LEARNING: A CONTAINER APPLICATION

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Abstract: Vessel berthing in a container port is considered as one of the most important application systems in the shipping industry. The objective of the vessel planning application system is to determine a suitable berth guaranteeing high vessel productivity. This is regarded as a very complex dynamic application, which can vastly benefited from autonomous decision making capabilities. On the other hand, BDI agent systems have been implemented in many business applications and found to have some limitations in observing environmental changes, adaptation and learning. We propose new hybrid BDI architecture with learning capabilities to overcome some of the limitations in the generic BDI model. A new "Knowledge Acquisition Module" (KAM) is proposed to improve the learning ability of the generic BDI model. Further, the generic BDI execution cycle has been extended to capture multiple events for a committed intention in achieving the set desires. This would essentially improve the autonomous behavior of the BDI agents, especially, in the intention reconsideration process. Changes in the environment are captured as events and the reinforcement learning techniques have been used to evaluate the effect of the environmental changes to the committed intentions in the proposed system. Finally, the Adaptive Neuro Fuzzy Inference (ANFIS) system is used to determine the validity of the committed intentions with the environmental changes.

1 INTRODUCTION

Shipping applications are heterogeneous, distributed, complex, dynamic, and large which, essentially requires cutting edge technology to yield extensibility and efficiency. One of the important applications in container terminals is the vessel berthing system. Vessel berthing application handles assigning berths to vessels, allocation of cranes, labor, trucks (loading and discharging) of containers assuring maximum utilization of resources and finally guaranteeing the high productivity of the terminal.

Most research papers carried out so far focus on the static berth allocation problem where the central issue is to allocate vessels waiting and arriving within the schedule window. Brown et al. (1994) used integer programming, Lim (1998) addressed the issue with fixed berth time, Chen and Hsieh (1999) used heuristic time space network model, Tong Lau and Lim (1999) used ant colony optimization approach, Yongpei Guan (2003) used heuristic worst-case analysis, Kim has used simulated annealing (Kim & Moon, 2003), but still fixed times are assigned to vessel operations and learning of data patterns are not considered in the decision making process.

On the other hand, intelligent agents are being used for modeling rational behaviors in a wide rage of distributed application systems. Intelligent agent receives various, if not contradictory, definitions; by general consensus, they must show some degree of autonomy, social ability and combine pro-active and reactive behaviors (Wooldridge, 1995). An obvious research problem is to devise software architecture that is capable of minimally satisfying the above requirements.

One solution in particular, that is currently the subject of much ongoing research, is the *belief-desire-intention* (BDI) approach (Georgeff, 1998). In some instances the criticism regarding BDI model has been that it is not well suited to certain types of behaviors. In particular, the basic BDI model appears to be inappropriate for building complex systems that must learn and adapt their behavior and such systems are becoming increasingly important in today's context in the business applications. Further,

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the generic BDI execution cycle will observe only one change or one event before it starts its intention reconsideration process. We believe if an agent could look ahead all the pending events which could cause any effect to the current intention, would essentially improve the autonomous behavior of the present BDI agent. Further, our proposed hybrid BDI agent architecture with improved learning capabilities would extend the learning and adaptability features of the current BDI agents. In this paper, we describe how dynamic changes in the environment are captured in the hybrid BDI agent architecture for the intention reconsideration process. Use of Adaptive Neuro Fuzzy Inference system (ANFIS) in the Hybrid BDI framework has indicated improved learning and decision-making capabilities in a complex, dynamic environment.

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 generic BDI agent architecture. Section 4 describes Plans used in the vessel berthing. Section 5 describes the hybrid BDI architecture. Section 6 describes reinforcement learning for the execution of plans. A test case is described in section 7 and conclusion is in section 8.

2 AN INTRODUCTION TO VESSEL BERTHING SYSTEM

Competition among container ports continues to increase as there are many facilities offered to improve the productivity of the calling vessels. Terminal operators in many container terminals are providing various services such as automating handling equipments, minimum waiting time at the outer harbor, improved target archiving mechanisms and bonus schemes etc, to attract many carriers. It is essential to adopt intelligent systems in identifying the appropriate ways of carrying vessel operations and most importantly in finding alternative plans and accurate predictions. In view of the dynamic nature of the application, we have enhanced the generic BDI model to behave as an intelligent agent with reasonably good prediction ability in handling vessel operations.

Shipping lines will inform the respective port the Expected Time of Arrival (ETA) and other vessel details. Changes to the original schedule are updated regularly in the Terminal. Arrival Declaration sent by shipping lines 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, etc. Vessel berthing application system of a container terminal should able to assign a suitable berth, cranes, people etc for the operations of the calling vessel. One of the primary objectives of the terminal operators is to assure the highest productivity, minimum waiting time at the outer harbor, earliest expected time of completion (ETC), earliest expected sailing time (EST), better utilization of resources such as Cranes, Trucks, labor etc in serving the new vessel.

Port of Colombo has been used as the test bed for our experiments, which handled approximately 1.8 million container boxes annually. The main container terminal is called the “Jaya container terminal” (JCT) which has four main berths called *jct1, jct2, jct3 and jct4.*

3 GENERIC BDI ARCHITETCURE

One of the most popular and successful agent based concepts is Rao and Georgeff [Rao and Georgeff, 1991], where the notions of Beliefs, Desires and Intentions are centrally focused and often referred to as BDI agents (Rao, 1991). Information about world is described in beliefs, such as *ETC, ETB* etc. Desires indicate the set of goals that an agent could achieve at a given in point in time. Agent would like all its desires achieved, but often desires are mutually exclusive. Therefore, agent should commit to certain desires called intentions.

BDI model has pre-defined library of plans. Sequence of plans is then executed in achieving the committed intention in the agent model. Changes to the environment are reflected in terms of events. Event-queue stores the sequence of events occurred during the execution of plans in the agent model. Generic BDI interpreter is shown in Figure 1 (Wooldridge, 1995). Algorithm indicated many limitations, in particular, it has assumed that the environment does not change after it observed the environment at step 3 (Wooldridge, 1995). Another limitation of the above algorithm is that the agent has overcommitted to its intention. i.e. all the plans which are belonged to the commiitted intention will be executed by the agents regardless of the envionmental chnages.

1. *$B=B_0$; $I=I_0$;*
2. *While true do*
3. *get next percept p;*
4. *B:= update beliefs ;*

5. *D:= option (B,I) ; /* get desires */*
6. *I:= select intentions (B,D,I)*
7. *π := plan (B,I) /* plan to be executed */*
8. *execute (π) ;*
9. *end while*

Figure 1: generic BDI interpreter

Wooldridge (1995) has shown improvements to the above limitations, but obseving many events at a given time was not described. In our paper we describe a extended algorithm with intelligent learning capabilities for improved decision making in complex applications. Plans required in a generic berthing application are described in the next section.

4 PLANS IN A VESSEL BERTHING SYSTEM.

Agents in the vessel berthing system require identifying *what* state of affairs that they want to achieve and *how* to achieve these states of affairs according to environmental changes. Set of desires are visible for an agent at a given time and should commit to one of the desires to achieve, which is called as an intention. Plans are recipes for achieving intentions. For example, when an event *ETA-received ( )* is observed by the agent, its desire should be to assign a suitable berth for the calling vessel assuring highest vessel productivity. There may be many desires that an agent could think of: *assign-berth (jct1), assign-berth (jct2), assign-berth (jct3) or assign-berth (jct4).* But practically agent would not be able to assign the calling vessel to all berths since all desires are mutually exclusive. Agent deliberation process should decide the most appropriate berth for the vessel operations and commit to it.

Option selected or intention should be achieved by executing a set of plans in the agent model. Figure 2 above shows a simple scenario of an example of such situation. Generic plans required in achieving the agent committed intentions in vessel berthing application are described in the next sub sections.

4.1 Sailing and Berth Drafts

Sailing and the berthing drafts of the new vessel (vbd^{vi} *and* vsd^{vi}) should be less than equal to draft of the respective berths (bdr_{bj}), that is

$$\forall i, j: \left[\left(vbd^{vi} \le vbr_{bj}\right) \wedge \left(vsd^{vi} \le bdr_{bj}\right)\right] \quad (1)$$

where, $1 \le i, j \le 4$.

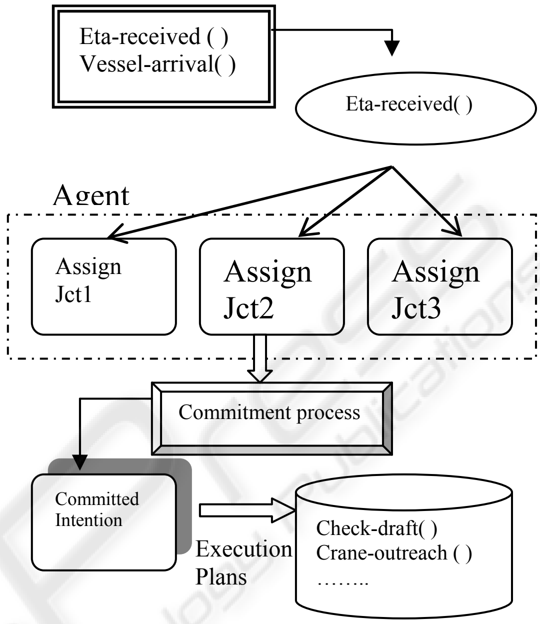

Figure 2: Execution of plans in the agent model.

4.2 Outreach of the Cranes in the Berth

Length of the cranes in the berth (len_{bj}^{ci}) should be equal or more to the vessel crane requirement (vcr^{vi}) i.e.

$$\forall i, j : \left(vcr^{vi} \le len_{bj}^{ci}\right) \text{ Where, } 1 \le i, j \le 4 \quad (2)$$

4.3 Average Crane Productivity of Berths

Individual berth should maximize the average crane productivity for calling vessels to gain the competitive advantage over other berths. Expected gross crane productivity of crane i in berth j for the new vessel *vi* is $gcp_{i,j}^{vi}$

$$gcp_{i,j}^{vi} = \frac{nob_i^{vi}}{\left|\left(cmo_{i,j}^{vi} - cpo_{i,j}^{vi}\right)\right|} \quad (3)$$

Average Crane productivity of the berth j for the vessel vi is given as

$$acp_j^{vi} = \frac{1}{n}\sum_{i=1}^{n} gcp_{i,j}^{vi}$$

(4)

Where $cmo_{i,j}^{vi}$ and $cpo_{i,j}^{vi}$ indicates the commencement and completion times of the crane *i* in berth *j* for the vessel *vi*. nob_i^{vi} and acp_j^{vi} indicates the number of boxes handled by crane i and expected average carne productivity in berth j for vessel vi. We have described few cases of plans required for the assignment of vessels in this paper due to the space limitation to describe our experimental results. Hybrid architecture proposed to improve the intelligent behavior of the BDI agents is described in the next section.

5 HYBRID BDI ARCHITECTURE

Intelligent learning while interacting with the environment is one of the primary objectives in developing hybrid BDI agents in our research. This would essentially minimize some of the limitations exists in the current BDI agents especially in complex dynamic application systems. It is also interesting to improve the agent behavior when observing environmental changes with uncertain data or information.

Two modules proposed in the hybrid BDI architecture are shown in Figure 3. "Generic BDI Module" (GBM) will execute the generic BDI interpreter as shown in Figure 1. "Knowledge Acquisition module" (KAM) provides the necessary intelligence for the execution of plans and finally to decide when to reconsider the committed intentions in the agent model (lokuge & Alahakoon, 2004). This would essentially assure dynamism in the allocation and reconsideration of committed intentions in the agent behavior.

A trained neural network in the KAM module enable agent to initially select the viable intention structures according to the beliefs and events in the environment. During the execution of plans for the committed intention, changes in the beliefs and their impact are investigated with the use of reinforcement learning techniques. ANFIS in the KAM module will finally decide whether it is required to reconsider the committed intentions or to continue with the same in achieving the desires of the system.

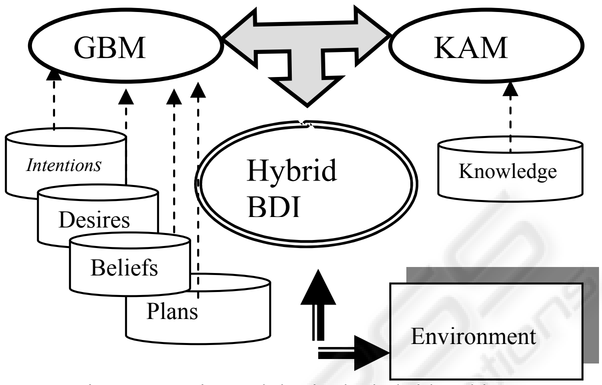

Figure 3: Main modules in the hybrid architecture

5.1 BDI Control Loop with Intention Reconsideration

Generic BDI execution cycle given in Figure 1 should be extended for the actual use in real time application systems. Wooldridge(2000) has extended the generic BDI execution cycle in number of ways which improves agent ability in replanting and intention reconsideration with the environmental changes. But agent ability in intelligent learning and use of intelligent knowledge in the generic BDI model are still not addressed in the literature. Agent should use previous experience in making rational decisions when ever it determines that its plans are no longer appropriate in order to achieve the current intentions, then it should engage further reasoning to find alternative ways to handle the situations.

Present BDI agent will always observe only the next available event before it commence the intention reconsideration process. This is a limitation in the present architecture which leads to delays in making correct decisions quickly. Ability to capture all the available events related to the committed intention would essentially help agent to look forward in many steps ahead before it proceeds with the intention reconsideration process. Also it does not say the agent ability to work with vague data sets and the implementation of present BDI model in such environments.

Proposed hybrid BDI architecture in this paper would address the above short comings in the present model and observed improved performances in the vessel berthing application. Extended hybrid BDI control loop with intelligent tools and observing multiple events is described in the next section.

5.2 Extended Hybrid BDI Control Loop

Hybrid BDI control loop with intelligence and leaning behavior is given in Figure 5. Intelligent tools such as neural networks and ANFIS in the proposed "KAM" module are used in choosing intentions and reconsideration of the committed intentions. Reinforcement learning techniques improve the interactive behavior of the proposed agent in executing plans for achieving the committed intentions. Most importantly, the above algorithm demonstrates the observation of multiple events which are related to the committed intention.

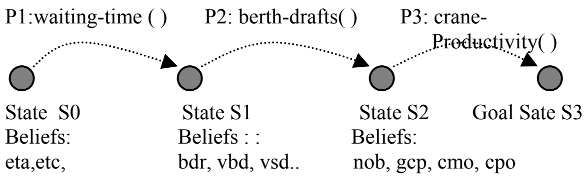

Figure 4: Plans in a committed intention

Let $S = \{s_i \mid 1 \le i \le n\}$ denotes n number of states in the environment. Any state s_i is described as a set of beliefs bel_i^I for an intention *I*. Execution of plans in various states results the change of state from one to another in the environment. Figure 4 above shows an example of states to be followed in achieving the committed intention *"assign-berth" at* a given time.

1. *$B=B_0$;$I=I_0$;*
2. *Define Belief-Impact-Matrix;*
3. *While true do*
4. *get next percept p;*
5. *B:= update beliefs( ) ;*
6. *D:= option (B,I) ; /* get desires */*
7. *INT:= KAM-intention (B,D,I) /* neural networks */*
8. *I:= Filter-intentions(INT); /* select an intention */*
9. *π^I := plan (B,I) /* plan to be executed */*
10. *Initialize-motivation matrix;*
11. *While not (empty-plan or intention-succeeded*
12. *or impossible-intention) do*
13. *α= head-of-the-plan( );*
14. *execute(α);*
15. $A^{I,t}_{(s,p)} = \left\{ \frac{E^{I,t}_{(s,p)}}{E^{m}_{(s,p)}} \times A^{m}_{(s,p)} \middle| s_t = s, p_t = p \right\}$
16. $V^I(s_t) \leftarrow V^I(s_t) + \beta \begin{bmatrix} A^{I,t}_{t+1} + \gamma V^I(s_{t+1}) \\ -V^I(s_t) \end{bmatrix}$
17. *event-filter ( ); /* observe multiple events */*
18. *B:= update beliefs ( ) ;*
19. $\Delta V_t(s_t) = \beta\left[R^n_t - V_t(s_t)\right]$
20. *Construct-vigilant-factor ( );*
21. *If ((vigilant-factor) $\ge$ T) then*
22. *IRT:= KAM-Intention-reconsideration ( )*
23. *end-if*
24. *If NOT(IRT) then*
25. *π^I := tail-of-plans ( );*
26. *end-if*
27. *end-while*
28. *end-while*

Figure 5: extended Hybrid BDI loop

Where $\beta\ \{0 \le \alpha \le 1\}$ is the learning rate and γ is the discount factor.

Belief-Impact-Matrix mentioned *(BIM)* in line 3, Figure 5 is required to analyze the effect of the belief changes for the execution of plans. BIM is given as :

$$BIM = \begin{bmatrix} \alpha^{I,p}_{1,1}\ \alpha^{I,p}_{1,2} \cdots \alpha^{I,p}_{1,k} \\ \cdots\cdots \\ \alpha^{I,p}_{l,1}\ \alpha^{I,p}_{l,2} \cdots \alpha^{I,p}_{l,k} \end{bmatrix} \tag{5}$$

$\alpha^{I,p}_{i,j}$ ($0 \le \alpha^{I,p}_{i,j} \le 1$) shows the impact factor or influence of the j^{th} belief in state *i* in the execution of plan *p* for the intention *I.* For example, change in expected time of completion of a berth (*etc*) does not have any effect on the execution of the plan *berth-draft( )* in states *S2,* and therefore, $\alpha^{I,p}_{i,j}$ should be zero for that instance in sate S2. . Some belief changes have higher impact on the committed intentions than others, which will be assigned values more closer to the upper bound of the $\alpha^{I,p}_{i,j}$. Line 7 indicates the use of a supervised neural network in the *"KAM"* module, which identify all the possible options in achieving the agent desire. Selection of the most viable option to commit is given line 8 of the algorithm. Calculation of rewards and the value of states due to the execution of plans will be described in the next section with the reinforcement learning techniques.

Event-filter ( ) in line number 17, will observe all the events occurred which have any impact on the committed intention that the agent is currently working with. This would enable hybrid agent to look forward in time to all the future belief changes for various states and then to decide the intention reconsideration process. Agent ability to observe multiple events in the environment and their effect to the committed intention is computed with n-step backup method in reinforcement learning as given in line 19. This enables event-filter ( ) to look forward in time to all future events in the event queue and estimate the distance change.

Since intention reconsideration process is a costly process, we have defined a *vigilant-factor* to avoid agent to reconsider its intentions at every possible moment. Also this would be used to control the sensitivity of the agent to environmental changes. Lower values for the threshold *T* make agent more sensitive to the environmental changes and vise versa. Use of reinforcement techniques for the execution of agent plans are described in the next section.

6 REINFORCEMENT LEARNING FOR AGENT PLANS

Temporal difference learning is a method to approximate the value function of states. The value of the present state can be expressed using the next immediate reinforcement and the value of the next state (Sutton, 1988). We use the temporal difference learning method to calculate the rewards receive and the value of states when executing plans for achieving the committed intentions in the hybrid model.

Lets assume, $E^m_{(s,p)}$ and $A^m_{(s,p)}$ are the expected and actual motivation values for the execution of plans p in state s, $A^{I,t}_{(s,p)}$ is the actual distance or reward computed based on the beliefs in the environment for the plans p in state s for the intention I and $E^{I,t}_{(s,p)}$ $\left(0 \le E^{I,t}_{(s,p)} \le 1\right)$ is the expected distance according to the motivation value in state s for the plan p. Then actual reward or distance due to execution of plan p in state s for a given intention I is given as:

$$A^{I,t}_{(s,p)} = r_{t+1} = \left\{ \frac{E^{I,t}_{(s,p)}}{E^m_{(s,p)}} \times A^m_{(s,p)} \middle| s_t = s,\, p_t = p \right\} \tag{6}$$

Therefore the value of a state *s,* after the execution of plan *p* for the intention *I* could be written as:

$$\begin{aligned} V_I^{\pi}(s,p) &= D_s^{\ I} = E^I{}_{\pi}\left\{R_t \middle| s_t = s, p_t = p\right\} \\ &= E^I{}_{\pi}\left\{\sum_{k=0}^{\infty} \gamma^k E^{I,t}_{t+k+1} \middle| s_t = s,\, p_t = p\right\} \end{aligned} \tag{7}$$

Once a plan has been executed, *event-filter ( )* process observe all the events in the event queue before the next plan is executed. BIM indicates the degree of the effect of the environment changes to the present state and agent then use ANFIS in the KAM module for the intention reconsideration process. Decision making power of the hybrid agent is improved as the estimation of value changes are dependent on all the belief changes in the environment.

Five layered adaptive neuro fuzzy inference system (Jang, 1993) is used in the proposed agent model to finalize the intention reconsideration process. Four linguistic variables are used in the decision making process of proposed model, namely, percentage of the distance change between time *t* and *t+1* due the environment changes *(θ_1),* Number of plans to be executed in achieving the committed intention *(θ_2),* number of plans already executed for the committed intention *(θ_3)* and finally, the effect or the criticality of the environmental changes *(θ_2)* for achieving the current intention. Past data of the decisions being made are used in the ANFIS in producing the membership functions for the above linguistic variables mentioned. A test case scenario in the next section describes the agent ability to handle multiple events in the intention reconsideration process in producing better results compared to the traditional BDI agent architecture.

7 A TEST CASE SCENARIO

Assume, that a vessel declaration event for the vessel Zim,”ETA-received ( )” is received at the JCT terminal, Port of Colombo, which minimally includes: vessel berth draft (vbd^{Zim})=12m, vessel sailing draft (vsd^{Zim})=12.1m, vessel crane requirement (vcr^{Zim})=13m, number of boxes (nob^{Zim})=752, expected time of arrival (eta^{Zim})=1300, length of the vessel (vln^{Zim})=292m etc.. JCT terminal has four main berths namely, jct1, jct2, jct3 and jct4. Beliefs at a given time in the environment are shown in the table 1. Expected operation time of vessels is denoted as ‘eot’ in the table.

Table 1: Beliefs of the environment

Beliefs	*Sea.L*	*Orient*	*Hanjin*	*Nord.L*
Berth	Jct1	Jct2	Jct3	Jct4
brd	11.3m	12.3m	14m	4m
len	13m	13m	18m	18m
acp	32.5mh	33.5mh	30.5mh	35.2mh
eot	22.9hrs	22.2hrs	24.4hrs	21.1hrs
etc	14:00	11:20	15:00	14:20

Berth Jct2 has been selected by the agent as it shows the highest productivity for the calling vessel and the set of plans executed and their state values computed from the reinforcement learning is shown the in table 2 below.

Table 2: Rewards computed for plans in Jct2

Plans	*Rewards*
P1 : Berth-drafts ( )	0.066
P2 : Vessel-distance-requirement ( )	1.0
P3: Waiting-time-vessels ( )	1.0
P4: Average-crane-productivity ( )	0.418
P5: Get-expected-operations-time ( )	0.18
value - state to goal - D_s	2.664

Value learned by temporal differential method in reinforcement learning for committed intention in assigning the vessel in Jct2 is given below in Figure 6. Figure shows the values approaches the actual state values when several time steps are used in the training.

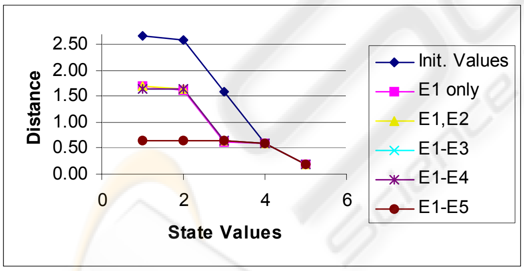

Figure 6: learning curves for states in Jct2

One of the membership functions produced and the decision surface produced from the ANFIS are shown in figure 7. Extended BDI algorithm given in the Figure 5 indicates that agent will observe events in the event queue before the execution of the next plan in the plan library.

Events in the event queue in a chronological order at a given time are shown below:

@ t - E1: "vessel-delay (Zim, eta=14.20, ...);
@ t+1 - E2:"change-in-etc (jct2, etc=12.30...);
@t+2 -E2: "sailing-draft-changed (Zim, vsd=14m.);
@t+3 - E4: "carne-productivity (jct1, 55.3mph...);
@t+4-E5:"crane-otreach(Zim,vcr=16m...).

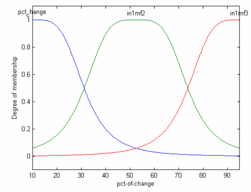

Figure 7 (a): membership function for percentage of distance change

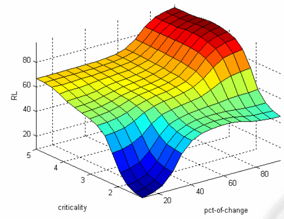

Figure 7 (b): Decision surface produced for percentage of distance change and criticality of the environment change

State values produced against the number of events considered are shown in Figure 8. When agent considers only the immediate event, i.e. *E1*, it does not indicate a strong impact on the committed intention and it may decide not to reconsider the current intention committed. But, actual scenario may be quite different to this. It is noted that the distance is largely changed when agent considers several future events. Observing the effects of all the available environmental changes before the next intention reconsideration process makes agents behavior more futuristic and dynamic.

Finally, the state values produced and the other three linguistic variables mentioned in the section 6 have been used in the ANFIS for the final intention reconsideration process. Table 3 indicates the intention reconsideration decision made by the ANFIS in the hybrid BDI model, where agent's prediction towards intention reconsideration is given as a percentage. Agent's ability to make more accurate decisions is improved with the increased number of events it observes in the environment. When agent considers the environmental changes due the occurrence of only event *E1*, ANFIS based KAM module indicate that only 12% support to drop the committed intention. But, if agent ever had a change to observe all the environmental chances due to the events in the event queue, its decision to continue with the current intention is deteriorated and indicates a 87.4% support that the current intention should be dropped. This is true as event *E4* indicates that crane outreach requirement of the vessel *Zim* has now changed to 16m, where the new requirement can not be fulfilled in the present berth

Jct2 (impossible to achieve). Therefore the current intention committed to assign the vessel *Zim* to berth *Jct2* should be dropped as indicated in the table.

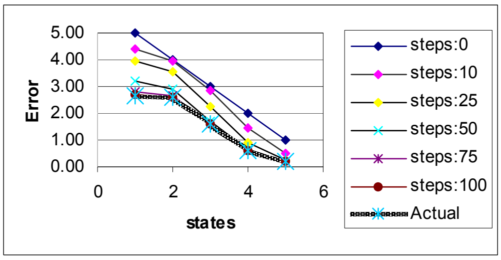

Figure 8: learning curves for states in Jct2

ANFIS output produced for events E1-E3 and E1-E4 given the same results as event E4 does not have any impact on the current intention and therefore agent has not considered that event in the intention reconsideration process.

Table 3: ANFIS output produced

	Events considered in the Intention Reconsideration				
	E1	E1,E2	E1-E3	E1-E4	E1-E5
ANFIS Output produced	12.4%	24.4%	85.3%	85.3%	87.4%

8 CONCLUSION

In this paper we presented an extended BDI control loop that enable to observe many events prior to decision making instead of one event which is the case in the present BDI architecture. Results of the intention reconsideration process have largely changed when agent observes many events trigged in the environment, which is found to be better and accurate. Agent decision making process has become faster and accurate compared to the present BDI architecture.

Also the agent ability to handle vague or uncertain data sets is also improved with the introduction of ANFIS in our "KAM" module. We believe that the intention reconsideration process could be further improved if agent could remember previously excluded options in the environment. This would enable agent to speedily work out the possibility of adopting those dropped options when ever the current one no longer valid in the present environment. Our future research work plans to further extend the BDI control loop enabling agent to compare different options in the intention reconsideration process.

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