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Marine Navigation Using Expert System

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ABSTRACT: A ship's autopilot adjustment is a matter of utmost importance since it affects its safety, command as well as fuel and time efficiency. A number of methods have been developed in order to cope with this issue usually based on models that simulate the weather conditions and adjust the device accordingly. Some of them have a considerable degree of success but none dealt with the problem completely. The main obstacles are the difficulty of simulating the infinite weather and loading conditions and to properly represent them with mathematical equations or rules. This paper describes a method of selecting the best out of a preexisting set of configurations, taking into account any weather situation, loading condition and type of ship. Moreover, the selected configuration can improve itself during the entire life cycle of the vessel, since it fine tunes its properties for better results. This approach uses Case Based Reasoning as its core technology and is a part of a hybrid system that analyses and solves prefixed problems of maritime interest.

1 INTRODUCTION

An autopilot is defined as a mechanical, electrical or hydraulic system used to guide a vehicle without assistance from a human being. A ship uses an autopilot for steering during her voyages except when she navigates in confined waters or maneuvering at port (COLREGS 72) **[8]**. A ship's voyage may last several days and a large proportion of it takes place in the open sea where the autopilot is used almost exclusively. Even though the ship's bridge, where the autopilot is located, is always supervised by the officer on watch (STCW 95) **[22]**, it is necessary to ensure that the autopilot is a safe and reliable tool in his / her hands.

Keeping a ship on course is not an easy task since ships are exposed to severe weather conditions and are operating in extreme situations. Wind, sea, current, etc, are some of the factors affecting a ship's deviation from the desired course. An autopilot's task is to keep the ship on track, not losing control in any case and simultaneously minimizing the deviations regardless of cause. To do that, an autopilot must have the proper configuration so that it would be able to perform its best according to the situation at hand. This ideal situation is not easy to achieve because the weather combinations of wind, sea, current, etc, are practically infinite and the same stands for the ship's loading conditions which also affect the final outcome. Moreover, an autopilot device is designed to work on almost any type of ship, thus its performance wouldn't be the same in different hulls.

The actual performance of the device is measured using parameters like loss of steering, vertical and angular deviation, extra distance, etc, because they are closely connected to dangerous situations at sea or significant losses of fuel and time. Loss of steering, combined with a generator failure can cause a serious accident i.e. capsize (Leontopoulos 79) **[34]**, while vertical deviation from course (Cross Track Error) leads to unwanted approaches to navigational dangers. Moreover, extreme angular deviations from compass settings affect the ability to command, especially in bad weather (Bowditch 2002) **[6]**. Finally, an incorrect adjustment increases the total voyage distance, the fuel consumption, the time delay and the corresponding costs (Dutton 1958) **[11]**.

Given the above it is very difficult to develop a method that takes into account all the affecting factors and being able to maximize the performance on every ship, under any weather and loading condition. An ideal situation would be the development of a customized device able to "understand" its environment (weather, loading condition and ship's particulars) and properly adjust itself, responding to any changes. Even though such a device is not developed yet, we claim that a pattern able to operate in a similar way is feasible, provided that a conventional device will be equipped with some additional features mentioned below.

This pattern is incorporated as an application within an AI system named POLARIS (**PO**licy **L**eading **AR**tificial **I**ntelligence **S**ystem) (Nikitakos & Fikaris, 2007) **[38]** able to analyze problems of maritime interest and propose courses of action for them. This approach has certain advantages compared to others because it doesn't deal directly with the identification and estimation of the parameter values that constitute a configuration but instead it presupposes an unlimited number of them already installed on the device, with known properties that can be modified according to the user's wishes. There is no limit to the number or nature of the parameters.

The system's core methodology is CBR (Case Based Reasoning) which solves current situations – problems with the assistance of similar cases that were dealt successfully in the past. These cases are stored in a case library and retrieved by the system using the proper indexes. The retrieved cases are ranked according to the criteria and the system proposes the best solution to solve the current problem. If necessary, a solution may be adapted to fit a new situation. When the best solution is proposed a procedure of fine tuning may begin and last till the solution meets the pre specified criteria.

The application described in this paper includes the development of a series of diagnostics performed by the autopilot device in different loading and weather situations in order to measure the corresponding performances and create a case base out of them. Thus, when the ship finds herself in a similar situation, the device will track the case's characteristics, select the case with the configuration that performed best and steer the ship with it until it detects another set of conditions. It is important to mention that the user may choose to measure the performance of a given situation again so that the database would be constantly updated with improved scores.

2 DSS AND CASE BASED REASONING

The literature defines Decision Support Systems (Raiffa 76) **[26]** as "interactive computer based systems that help decision-makers use data and models to solve ill-structured, unstructured or semi-structured problems (Goel 92) **[15]**." The most popular definitions belong to Gorry & Scott-Morton (1971) **[16]**, Keen and Scott-Morton (1978) **[25]** and Bonczek, Holsapple & Whinston (1981) **[5]**. DSS were categorized in seven major categories which are file drawer systems, data analysis systems, analysis information systems, accounting and financial models, representational models, optimization systems and suggestion systems (Alter 1980) **[1]**. A type based categorization defines data driven, model driven (Knowles 89) **[28]** and knowledge driven systems (Dhar & Stein 1997 **[9]**, Holsapple & Whinston 1996) **[20]**).

Knowledge driven DSS -sometimes called Expert Systems- incorporate knowledge about a particular domain, understanding of problem solving and expertise at solving those problems (Redmond 1992) **[42]**. They are also related to data mining techniques and usually evolve to hybrid systems (Simpson, 1985) **[44]**. Major components of a DSS are a) the shell b) the case library c) the knowledge base or the model and d) the system's architecture and network (Sprague and Carlson 1982) **[46]**. These systems analyze data using symbolic logic, have an explicit knowledge base and have the ability to explain conclusions in an understandable way. Web based DSS are referring to a computerized system that delivers decision support information or decision support tools to a manager or business analyst using a "thin client" Web browser (Power 2000) **[41]**.

Reasoning is a procedure that draws conclusions by chaining together generalized rules, usually starting from scratch. However in Case Based Reasoning new solutions are generated not by chaining, but by retrieving the most relevant cases from memory and adapting them to fit new situations (Leake 1996, 2003) **[33][32]**. A case is a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner. A case may have different shapes or sizes, various time horizons and can associate solutions with problems, outcomes with situations or both. A case's main task is to provide a solution to a problem but it can also provide the necessary context to assess or understand a situation (Kolodner 93, Schank 1994) **[29]** **[45]**. A case is comprised from indexes which should be predictive, goal oriented, abstract and easily recognizable (Birnbaum & Collins 89 **[4]**, Hammond 89 **[18]**). These indexes must describe the problem (goals, constraints and situation), the solution and the outcome. The case base indexing is organized according to the problem's requirements and can be checklist based, difference based (Kolodner 93) **[29]**, similarity and explanation based (Hammond 87, 89 **[17]**), etc. The problem / situation indexes are mainly used for the retrieval, qualification and ranking of cases while the solution indexes present the way of action to the user. The outcome indexes are a part of the evaluation procedure.

The main advantages of CBR are its simplicity, its capability of incorporating uncertainty and its plausibility (Kolodner 1993) **[29]**. Two major classes of CBR systems have been developing since the method's introduction. These are the interpretive and problem solving CBR systems (Rissland, Kolodner & Waltz, 1989) **[43]**. The former use prior cases as reference points for classifying new situations, whilst the latter use prior cases to suggest solutions that apply to new circumstances. Another major advantage of CBR is that because it uses specific episodes (cases) for reasoning there is no need to develop many rules and thus makes the knowledge acquisition process –which is vital to AI systems- very "cheap". As pointed by "Mark et al, (1996)" **[35]** there are some domains that are very suitable for CBR, while others are not, especially if cases are unavailable or in hard to use format. The functions performed by a typical CBR system are recall and interpretation of past experiences (cases), adaptation of those cases to fit the new situation, evaluation of proposed solutions and repair of the "defective" ones (Kolodner, 1993) **[29]**.

POLARIS is an AI system containing elements of a DSS since it interacts with the user and helps him find the best out of a series of alternatives as well as expert knowledge relevant to the problem's domain. The system uses data from old cases to solve new problems but it also incorporates expert knowledge from the problem domain. Thus, its type is a mixture of a data and knowledge driven system strongly dependent on the nature of the application. All these are significantly affected by the complexity of the problem and the domain knowledge available. The system's architecture follows the CBR procedures and comprises of the following modules:

- User interface: interacts with the user
- Case Library: contains the old cases
- Knowledge base: contains the expert knowledge in the form of rules
- Case Retriever: retrieves and ranks the useful cases
- Solution presentation facility: presents the solution to the user
- Solution evaluator: evaluates the solution after the implementation
- Solution adaptor: adapts the solution to fit the current situation
- Case storage facility: stores new cases to the library (Moorman & Ram, 1992) **[37]**

3 ADJUSTMENT METHODS REVIEW

A quick review of the methods used in order to properly adjust a ship's autopilot shows that almost every single AI technology was used by a number of researchers. Fuzzy logic (Polkinghorne M.N; Burns R.S 1994 **[39]**, Roberts G.N, Roberts and Sutton 2006 **[40]**), Neuron Networks (Unar and Murray-Smith 1999 **[48]**, Jia, X.J Yang and X.R Zhao, 2006 **[49]**), Optimization techniques (Holzhuter, 1997) **[21]**, Linear programming (Goheen K.R, Jeffreys E.R, 1990 **[31]**), Model Based Reasoning (Honderd and Winkelman, 1972 **[14]**, Van Amerongen and Udink ten Cate, 1975 **[23]**, Van Amerongen and Van Nauta Lemke, 1986 **[24]**), Self tuning regulators (KJ Astrom et al, 1977 **[27]**), Stochastic models (Ohtsu et al, 1979 **[30]**, Herther et al, 1971 **[19]**), etc, represent only a fragment of the work that has been done in the field.

Most Autopilots are adjusted using the PID controller which calculates a performance variable with known values and applies the necessary corrective actions based on the difference between the calculated and expected value. The controller includes three parts: The first one responds to the error, the second applies a correction for the sum of all the errors and the third responds to the error variation percentage. PID controllers however cannot perform in non linear systems and their accuracy is very low.

Another interesting work is the one of Unar and Murray-Smith who developed an artificial neural network which controls and coordinates a series of conventional controllers. Each controller is manufactured for a specific operational situation of the vessel. Still, the level of detail is low and the situation coverage very poor. Moreover, the system's cost and maintenance is relatively high. This approach has some similarities with CBR since each controller represents a situation, but it is obvious that the number of controllers is finite and cannot cover the infinite weather and loading situations.

4 THE AUTOPILOT APPLICATION THEORY

The Autopilot application presupposes a finite number of configurations available on the device and a number of known parameters which are adjustable and affect the configuration significantly. The system creates a case library performing a series of trials, assessing each configuration's performance for a given situation. The situations and the corresponding performance values are stored in memory and ideally some time during the ship's life cycle there will be a case for almost every combination of weather and loading condition.

When the ship's devices detect a specific weather situation, and given that the loading data as well as the ship's particulars are already stored in memory, the system retrieves the cases with the best performance values from the base. The qualified cases are ranked and the corresponding configuration is presented to the user. After the implementation of the selected configuration the system records the actual performance and compares it with the expected one. If the actual performance is not satisfactory the system either switches to the second best configuration or it enables a fine tuning procedure where it performs a sensitivity analysis of every parameter in the selected configuration aiming to achieve a better performance. If this is accomplished it stores the new set of parameters and the corresponding performance indicators, thus creating a new configuration for the device.

The Autopilot's case contains six categories of indexes which represent the performance criteria (goals), the weather conditions (situation), the loading condition of the ship (situation), the ship's particulars (user characteristics), the configuration used (solution) and the applied performance criteria (outcome).

4.1 *Performance Indexes*

The performance indexes (criteria) mainly cover the dimensions of danger, ease of command, cost and time. Three variables have been used. The first one is the difference of the distance measured by the ship's track to bottom from the rhumb line distance between waypoints (*d*). The second is the maximum (*dmmax*) and mean vertical deviation to course (XTE) in miles (*dm*) while the third is the maximum (*ddmax*) and mean deviation of the ship's bow to the true course in degrees (*dd*). Loss of steering $LS > 0$, *dmmax>threshold1* and *ddmax>threshold2* were set as hard constraints. The system is able to automatically calculate all these quantities either separately with the appropriate sensors either using the usual bridge electronic equipment (GPS, ECDIS & ARPA combined) provided that they are connected to the improved Autopilot device.

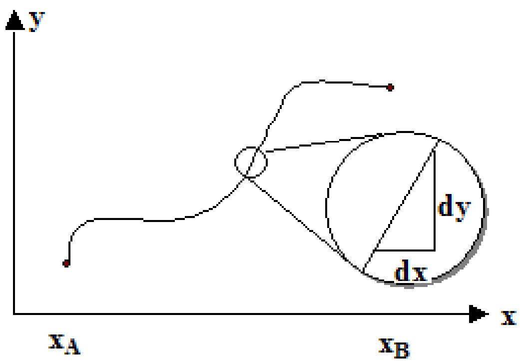

Figure 1: True distance of ship's track to bottom

The first criterion *d* was selected because it represents the extra distance traveled by the ship in a given part of the journey, so it can be translated to extra fuel and time that is monetary cost. The true distance (Figure 1)[1] is calculated using the formula

$$\lambda = \int_{\alpha}^{\beta} \sqrt{1 + \left(\frac{d\psi}{d\chi}\right)^2}\, d\chi$$

The rhumb line distance is k = (ΔΦ)' secZ whereas Z : true course, so the first criterion equals:

$$d = \int_{\alpha}^{\beta} \sqrt{1 + \left(\frac{d\psi}{d\chi}\right)^2}\, d\chi - (\Delta\phi)' \sec Z$$

Similarly the second criterion's hard constraint is $dm\max = A \tan(\max RB)$ whereas A: ship's advance from extreme vertical XTE point E_i till the next point C_i where it meets the course again and max RB: maximum relative bearing to point E while the mean is calculated as:

$$dm = \sum_1^p A^* \tan RB / \, p$$

where p is the number of selected and calculated XTE points. This criterion expresses the ship's mean XTE from course, thus it's an indicator of possible approaches to navigational dangers like shallow waters, wrecks, etc. The third criterion and the hard constraint that derives from it are:

$$dd = \sum_1^p \left|Z\max - Z\right| / \, p \text{ and } dd\max = \left|Z\max - Z\right|$$

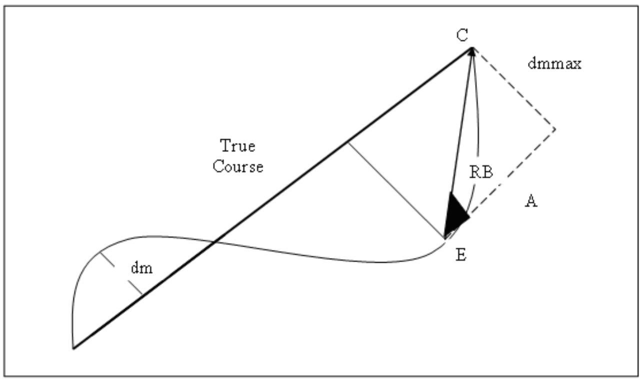

Figure 2: Vertical deviation – Max and mean

These express the selection's performance in steering or the ship's "swinging" on either side (Leontopoulos 1979) **[34].** Those criteria were combined to measure the negative performance of each alternative. The analysis[2] assigned 5 negative points for each extra mile, 10 points for each XTE mile and 0, 2 for each degree of deviation. Moreover, the two hard constraint thresholds were set to 0.02 miles / Beaufort for *dmmax* and 2 degrees / Beaufort for *ddmax*. Dmmax is increased by 20% for each knot of current with a relative bearing > 45°. These are default values and are justified after a survey with experts aiming to assess the severity of each criterion as far as the autopilot device is concerned. If the user disagrees he / she can intervene and change this balance by inserting values to the coefficients α, β, γ assigned to each criterion during the interaction with

[1] Axis x refers to geographical longitude and axis Y to latitude

[2] The thresholds are for a 65000 DWT Panamax bulk carrier. For other types of ships the numbers are different, slightly increasing with the tonnage

the system. After the normalization the selection's negative performance is calculated as follows:

$$NP = a\left[\left(\int_{k}^{lb}\sqrt{1+\left(\frac{d\psi}{d\chi}\right)^{2}}\,d\chi\right)-(\Delta\phi)'\sec Z\right]+$$
$$+\beta\left(\sum_{1}^{p} A^{*}\tan RB\right)/\,p+\gamma\left(\sum_{1}^{p}\left|Z\max-Z\right|\right)/\,p$$

4.2 *Wheather condition indexes*

The weather condition indexes describe the wind, sea and current. The case includes wind direction and force, sea direction and force, current direction and speed as well as swell direction and height. All directions are expressed in degrees, wind and sea force in Beauforts, current speed in knots and swell height in meters. All directions are relative to bow and current speed is true. A situation is considered identical when the parameter differences will not exceed half of a preset allowance in either direction (+/-). As the case library grows bigger the boundaries can be stricter for better accuracy.

The weather situation is expressed by four major phenomena which are wind, sea, current and swell. Sea condition will always be a part of the situation during the retrieval procedure, while current, swell and wind can be omitted if there are not any exact matches. If the phenomenon is to be included in the case retrieval process, its indexes are analyzed further in order to determine their actual importance and whether they should be included as retrieval criteria. Table 1 shows a strict version of the retrieval process because the criterion used is the existence of a Medium importance (M) characterization for the relative course or the sea force. Relative course has three importance levels (Low, Medium, and High) covering 30 degrees from bow and sea force has six levels (Very Low, Low, Medium, High, Very High, and Extremely High) each covering two Beauforts. As seen in table 1, in almost all cases the sea indexes should be included in the retrieval. The lower part presents the same data but now the criterion is the existence of a High importance (H) in any of the two indexes.

Table 1: Combined importance of sea direction and force (Medium and High Importance Thresholds are set)

	1 – 2	3 – 4	5 – 6	7 – 8	9 – 10	11 – 12
0 - 30	L-VL	L-L	L-M	L-H	L-VH	L-EH
31 – 60	M-VL	M-L	M-M	M-H	M-VH	M-EH
61 – 90	H-VL	H-L	H-M	H-H	H-VH	H-EH
91 – 120	H-VL	H-L	H-M	H-H	H-VH	H-EH
121 – 150	M-VL	M-L	M-M	M-H	M-VH	M-EH
151 – 180	L-VL	L-L	L-M	L-H	L-VH	L-EH
181 – 210	L-VL	L-L	L-M	L-H	L-VH	L-EH
211 – 240	M-VL	M-L	M-M	M-H	M-VH	M-EH
241 – 270	H-VL	H-L	H-M	H-H	H-VH	H-EH
271 – 300	H-VL	H-L	H-M	H-H	H-VH	H-EH
301 – 330	M-VL	M-L	M-M	M-H	M-VH	M-EH
331 - 360	L-VL	L-L	L-M	L-H	L-VH	L-EH

	1 – 2	3 – 4	5 – 6	7 – 8	9 – 10	11 – 12
0 - 30	L-VL	L-L	L-M	L-H	L-VH	L-EH
31 – 60	M-VL	M-L	M-M	M-H	M-VH	M-EH
61 – 90	H-VL	H-L	H-M	H-H	H-VH	H-EH
91 – 120	H-VL	H-L	H-M	H-H	H-VH	H-EH
121 – 150	M-VL	M-L	M-M	M-H	M-VH	M-EH
151 – 180	L-VL	L-L	L-M	L-H	L-VH	L-EH
181 – 210	L-VL	L-L	L-M	L-H	L-VH	L-EH
211 – 240	M-VL	M-L	M-M	M-H	M-VH	M-EH
241 – 270	H-VL	H-L	H-M	H-H	H-VH	H-EH
271 – 300	H-VL	H-L	H-M	H-H	H-VH	H-EH
301 – 330	M-VL	M-L	M-M	M-H	M-VH	M-EH
331 - 360	L-VL	L-L	L-M	L-H	L-VH	L-EH

The influence of the sea condition parameter is affected by a lot of things, but since the case refers to the same ship, the only other factor to be considered is the loading situation. Sea direction and force has a much greater impact when the ship is on ballast and less when it's fully loaded. Thus, when the vessel is on ballast condition more weather combinations should be included. The strict version is used for ballast condition and the less strict for the fully loaded condition. Further division i.e. semi loaded condition can be applied if needed.

Current, swell and wind are represented similarly in the knowledge base. Importance weights were assigned to each direction for each one of the three phenomena. Current was given a scale of 0 – 10 knots ranging from Very low to Very High importance with a pace of 2 knots. The existence of a Medium importance is the criterion when the ship is on ballast condition while a value of High importance is necessary when the ship is loaded. Swell is measured with a scale of 0 – 5 meters ranging from Very Low to Very high importance while wind has the same scale as the sea. The thresholds are at least one Medium importance for the ballast and at least one High importance for the fully loaded condition.

4.3 *Loading condition and ship particulars indexes*

The loading condition indexes include information about the deadweight, draft, trim, declination, LCG, VCG, TCG, free surfaces, hogging and sagging. Additional indexes include the capacity used, type of cargo, fuel, ballast, supplies or alternative ones like hull coefficient proportions, stowage factors, etc. The ship's particulars represent the user characteristics and include the basic dimensions, ship's coefficients, RPM (sea speed), rudder elements, maneuvering characteristics, etc. The loading condition and the ship particulars indexes are presented in table 2.

Table 2: Loading condition and ship particulars indexes

Index	Description	Importance	Index	Description	Importance
C%	Cargo percentage	High	Hog	Hogging	Low
d	Draft	High	Sag	Sagging	Low
δ	Trim	High	SF	Stowage Factor	High
dec	Declination	Medium	U	Ullages	Medium
LCG	Longitudiotal C.G	Medium	F%	Fuel percentage	Low
VCG	Vertical C.G	High	B%	Ballast percentage	High
TCG	Transverse C.G.	Medium	S%	Supplies percentage	Low
Io	Free Surfaces	Medium			

Index	Description	Importance	Index	Description	Importance
LOA	Length overall	High	RPM	Revolution per min	High
MaxB	Max breadth	High	Pitch	Propeller pitch	Low
Hgt	Height	Low	Prop	Propeller turn	Low
Cx	Hull coefficient	High	Rud	Rudder surface	High
Ca	Frame coefficient	Medium	Bulb	Bulbous buoy	Medium
Cw	Water plate coeff	High	Stern	Stern type	High
Cp	Prismatic coeff	High			

The loading indexes are identified after interviews with merchant ship masters and deck officers with more than adequate experience in the field. Importance weights have been assigned to each one of them in order to identify those necessary to be included as criteria in each retrieval procedure. The indexes with the highest importance are the DW, d, δ, dec, VCG, Io, SF and the Ballast percentage. All others are already covered by them and exist for accuracy reasons. It should be noted that any of these indexes can be omitted if the user wishes to or if the case library is not rich enough and cannot retrieve exact matches. Also, the value boundaries can change to permit a stricter or a more loose retrieval in accordance with the needs.

The ship's particulars indexes describe the user (ship) characteristics. Even though the Autopilot application refers to the same ship the particulars are inserted in the library in case a possible user company decides to integrate the fleet's libraries to create a richer one, especially if there are vessels with similar characteristics. Like every category of indexes and as the case library grows more indexes can be added or stricter criteria can be set.

4.4 *Solution and outcome indexes*

In this application the solution parameters are only the configuration with the best performance and its corresponding characteristics. For simplicity reasons we included two attributes (for demonstration purposes only) which are the angular velocity of the rudder (AVR) and the rudder angle permitted (RA) in order to keep the ship on course. The configurations available can be any combination of these values, thus for AVR values $n-2$, n and $n+2$ degrees per second and RA values of $k-5$, k and $k+5$ degrees we have 9 possible combinations, plus a ($n - 4, k - 10$) combination for very calm sea. Finally, the outcome indexes are the same as the criteria indexes, but their values will be the actual performance of the configuration during the voyage.

4.5 *Case Retrieval*

Case retrieval is one of the most important parts of the system's reasoning since it is required to select all the related cases, classify them according to their utility towards the goals and promoting the most promising of them. As mentioned in the literature the proper retrieval requires a degree of similarity between the new and the retrieved situation. Many CBR systems use various levels of abstractions in order to recognise similarities between cases of different domains. There are numerous algorithms used for the case retrieval strongly dependent on the problem complexity. Usual serial algorithms are the Flat memory – serial search enhanced with shallow indexing, case library partitioning or synchronous parallel retrieval (Kolodner 93) **[29]**, Shared Featured Networks (Fischer 87 **[13]**, Michalski and Stepp 83 **[36]**, Cheeseman 88 **[7]**, Quinlan 86), Discrimination Networks (Feigenbaum 63) **[12]**) and Redundant Discrimination Networks (Kolodner 93) while parallel algorithms are Flat Library – Parallel search (Stanfild and Waltz 81, 88 **[47]**, Simoudis 91, 92, Domeshek 89, 91 **[10]**), Hierarchical memory – Parallel search (Kolodner 93) **[29]**. A serial search is used for the Autopilot application assisted by a case library partitioning using the sea condition indexes. Other situation parameters can be used in case the library grows very big.

When the system detects the cases whose values fall into the ranges permitted it uses the nearest neighbour approach (Dasarathy 1991) **[3]** for each selected characteristic in order to assess the degree of situation similarity. This leads to the retrieval of a set of cases which are ranked according to the criteria. In the Autopilot's knowledge base the priorities are safety, command and monetary cost, so the goals are ordered with this logic: Loss of steering, vertical deviation, angular deviation and finally difference of distance. The system rejects any case that violates a hard constraint and then calculates the negative performance of the remaining cases, proposing the one with the lowest score to the user.

4.6 *Evaluation and adaptation*

The evaluation procedure is the comparison of the actual performance of the configuration used with the one stored (the best) in the case library. If the performance is not satisfactory the user has two choices. One is to select the second best configuration for the specific situation and store it in memory and the second is to adapt the selected configuration to fit the new situation. This is done by initiating a fine tuning procedure (or sensitivity analysis) where the system changes the configuration parameter values and performs a new series of diagnostics in order to track the adapted configuration with the best performance. In the Autopilot application the system assesses the performance of the adapted configurations relatively easy since the parameters are only two (AVR & RA) and the possible combinations no more than ten. Of course the configuration parameters can be much more, with the system's processing time increasing exponentially but then, fuzzy logic classifications can be used to reduce the processing time. One way to avoid that is to categorize the configurations in classes and further examine them if the performance is not adequate.

There is no adaptation procedure in this particular applcation because the suggestion's outcome is an already preset configuration with fixed attributes. Moreover, instead of trying to modify the reasoning or re configurate the solution, it is far more preferable to simply use the second or third best configuration proposed by the system or re run the diagnostics with less strict constraints.

5 CASE STUDY

A 65000 DWT bulk carrier was selected for this case study which is presented based on real voyage data except the values of the performance criteria, since such a device is not developed yet. The ship sailed from Los Angeles (USA) to San Bernardino (Philippines) and performed its diagnostics during a great circle trip. The ship is loaded with corn and travels at usual sea speed. We suppose there is an autopilot on board that has 10 different selections, so the diagnostic test will be performed 10 times in each part of the great circle given that every part has significantly different weather conditions. If this ideal situation occurs a case base of 10 X 11 = 110 cases will be constructed in a single trip. The great circle data are shown in table 3. It must be noted that the rest of the case study is focused to the first way point for simplicity reasons, since the procedure is similar for every other part of the voyage. The distance set for each selection is 10 miles, thus the first test will cover a total distance of 100 miles.

A general description of the voyage is as follows: The ship's draught was 13.3 meters, the cargo holds were full and the stowage factor was 1.52. There was no hogging or sagging and the trim was 1 meter by the stern. The engine's RPM were 110 and the ship's initial stability satisfactory since the GM was 25 centimeters. The ship's heading was 295 during the first diagnostic and the wind was NW 6-7. The sea was NNE moderate to rough and the current 2 knots to the starboard beam.

Table 3: Initial voyage data

Initial data	Way Point Data			
	DepLat	DepLong	ArrLat	ArrLong
Departure Lat: 34° 00′ N	34 00 N	120 40 W	37 16 N	130 00 W
Departure Long: 120° 40′ W	37 16 N	130 00 W	39 31 N	140 00 W
Arrival Lat: 12° 45′ N	39 31 N	140 00 W	40 51 N	150 00 W
Arrival Long: 124° 20′ E	40 51 N	150 00 W	41 19 N	160 32,7 W
Great circle dist: 6156,6 m	41 19 N	160 32,7 W	40 51 N	170 00 W
Rhumb line dist: 6446,6 m	40 51 N	170 00 W	39 31 N	180 00
Great circle diff: 290 m	39 31 N	180 00	37 16 N	170 00 E
Initial course: 295°	37 16 N	170 00 E	33 56 N	160 00 E
Vertex Lat: 41° 19′ N	33 56 N	160 00 E	29 25 N	150 00 E
Vertex Long: 160° 32,7′ W	29 25 N	150 00 E	23 42 N	140 00 E
Vertex dist: 1927 m	23 42 N	140 00 E	16 42 N	130 00 E
	16 42 N	130 00 E	12 45 N	124 20 E

The situation was presented with two sets of variables –weather and loading parameters- and a third set which is already inserted in memory representing the ship's particulars. The variables used for the weather conditions are the relative directions of sea, current, wind and swell and are listed in table 4. The weather situation is identical since the heading and distance traveled for each test is the same (295, 10), the wind[3], sea and current differences do not exceed the allowances permitted and there is not any swell. The loading situation was represented using the cargo (+/- 25*TPC[4] % MT), draft (+/- 0, 25 m), SF (+/- 0, 05), % hold capacity (+/- 10%), RPM (+/- 2%), VCG (+/- 0, 05 m) and trim (+/- 0, 5 m) variables. The parentheses show the allowances for the loading situation similarity. The loading situation is shown in table 5. Table 6 shows the case as it is stored in the case library.

Table 4: The weather conditions during the diagnostic test

Diagnostic Selection	Wind Rel. Dir.	Wind Force	Sea Rel Dir	Sea Force	Current Rel Dir	Current Speed	Swell
1.1	-35	6	85	5	85	1,5	No
1.2	-40	7	90	6	90	2	No
1.3	-30	7	90	6	90	2	No
1.4	-35	7	90	7	90	2	No
1.5	-45	6	100	6	95	1,5	No
1.6	-35	6	100	5	95	1,5	No
1.7	-20	7	100	6	95	2	No
1.8	-35	6	100	5	95	2	No
1.9	-25	6	100	6	95	2	No
1.10	-35	6	105	6	100	2	No

Table 5: The loading condition during the diagnostic test

Index	Description	Index	Importance
C%	100 %	Hog	Not used
d	13,3	Sag	Not used
δ	-1	SF	1,52
dec	0	U	Not used
LCG	Not used	F%	Not used
VCG	0,25	B%	0 %
TCG	Not used	S%	Not used
Io	Not used		

[3] The (-) declares left (port) from bow

[4] Tons Per Centimeter: the amount of cargo required to alter the ship's draft for 1 centimeter

Table 6: The situation as it is stored in the base

Diagnostic Selection	Wind Rel. Dir.	Wind Force	Sea Rel Dir	Sea Force	Current Rel Dir	Current Speed	Swell	Displ
1.1	-35	6	85	5	85	1,5	No	No
1.2	-40	7	90	6	90	2	No	No
1.3	-30	7	90	6	90	2	No	No
1.4	-35	7	90	7	90	2	No	No
1.5	-45	6	100	6	95	1,5	No	No
1.6	-35	6	100	5	95	1,5	No	No
1.7	-20	7	100	6	95	2	No	No
1.8	-35	6	100	5	95	2	No	No
1.9	-25	6	100	6	95	2	No	No
1.10	-35	6	105	6	100	2	No	No

Selection	Displ	Hull C	Draft	SF	Capac.	GM	Cargo	RPM	Io	Trim	Hog	Sag
1.1	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.2	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.3	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.4	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.5	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.6	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.7	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.8	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.9	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0
1.10	No	No	13,3	1,52	100	25	Grain	110	0	-1	0	0

Table 7 presents a scenario of possible criteria values measured during the diagnostics. These include the criteria measuring the performance as well as the hard constraints with their respective thresholds. The first hard constraint eliminates three selections since the maximum vertical distance dmmax exceeds the threshold dmmaxTh. Thus, selections 1.1, 1.2 and 1.3 are no longer considered. Similarly the second constraint ddmax eliminates the selections 1.6 and 1.10 since the value must be below the limit and not equal. The third constraint which requires zero tolerance to steering losses eliminates selections 1.6 and 1.7 as well as 1.2 and 1.3 which were already excluded. At this point selections 1.4, 1.5, 1.8 and 1.9 remained active and the system calculates their negative performance NP in order to rank them. Finally, selection 1.8 is proposed as the best alternative since it has less negative points than the others.

Table 7: Criteria and hard constraints

Selection	d	dm	dmmax	dmmaxTh	dd	ddmax	ddmaxTh	SL	NP
1.1	0,8	0,1	**0,12**	0,1	9	11	12	0	6,8
1.2	1,2	0,15	**0,18**	0,12	13	**15**	12	**1**	10,1
1.3	0,9	0,12	**0,13**	0,12	11	**13**	12	**1**	7,9
1.4	0,5	0,05	0,07	0,14	10	12	14	0	**5**
1.5	0,3	0,02	0,04	0,12	5	7	12	0	**2,7**
1.6	0,6	0,055	0,07	0,1	8	**10**	10	**1**	5,15
1.7	0,7	0,06	0,08	0,12	9	11	12	**1**	5,9
1.8	0,3	0,02	0,03	0,1	4	6	10	0	2,5
1.9	0,3	0,025	0,04	0,12	5	6	12	0	**2,75**
1.10	0,8	0,11	0,12	0,12	13	**15**	12	0	7,7

An estimation of the potential benefits resulting from a proper selection is shown comparing the better with the worst alternative not taking into account the hard constraints that exclude it. Those alternatives are 1.8 and 1.2. Criterion d shows that the ship travels 0, 9 extra miles[5] in every 10 miles of journey. This means that during this passage the ship will travel 6156, 6 * 0, 9 / 10 = 554 extra nautical miles and will lose 554 / 15 = 37 hours in terms of time. Moreover the ship will vertically deviate (mean) from its course 278 meters more and swing about 10 degrees more (mean) if 1.2 is selected. This means bigger exposure to danger and greater difficulty in command which in turn wears the hull, engine, propeller, etc. One must not forget the additional wear and tear of the rudder and engine if a false steering configuration is set as well as the crew fatigue and other damages that may result from rolling, pitching, etc.

6 CONCLUSION – FUTURE RESEARCH

Summarizing the above it is concluded that a way of selecting the best alternative from a pre existing set of configurations of an autopilot is possible using CBR as the core technology. Since such a device is not yet developed this application is considered conceptional and its main task was to present some initial thoughts still requiring verification and hard data. The development of a prototype could give a lot of answers and test the system's performance in the real world.

Apart from that we strongly believe that the maritime industry and especially the ship is a very compatible environment for CBR and numerous applications could be developed. In time, an integrated system able to deal with a number of issues could be developed and with the accumulation of cases its performance and learning will constantly improve.

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[5] Additional miles travelled if instead of the best, the worst performing configuration is selected by the device

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