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# Development of Case-adaptation Algorithm using Genetic Algorithm and Artificial Neural Networks

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## Abstract

In this research, hybrid method with case-based reasoning and rule-based reasoning is applied. Using case-based reasoning, design experts' experience and know-how are effectively represented in order to obtain a proper configuration of midship section in the initial ship design stage. Since there is not sufficient domain knowledge available to us, traditional case-adaptation algorithms cannot be applied to our problem, i.e., creating the configuration of midship section. Thus, new case-adaptation algorithms not requiring any domain knowledge are developed and applied to our problem. Using the knowledge representation of DnV rules, rule-based reasoning can perform deductive inference in order to obtain the scantling of midship section efficiently. The results from the case-based reasoning and the rule-based reasoning are examined by comparing the results with various conventional methods. And the reasonability of our results is verified by comparing the results with actual values from parent ship.

**Keywords: case-based reasoning, rule-base reasoning, initial ship design, case-adaptation algorithms, direct mapping algorithm**

## 1 Introduction

An initial ship design starts by selecting one or two parent ship among the past-constructed ships with a consideration of owners' requirement. And then, the principal dimensions and various coefficients are estimated using a proper empirical formula and design experts' know-how. In succession performed is a series of jobs such as an estimation of lightweight and propeller power, selection of main engine, rough arrangement of compartment, and an initial design of hull form. Only when all these tiresome jobs are done, a proper configuration of midship section can be obtained. Since much of the information is uncertain and complex especially in the early design stage, the designers use rules-of-thumb based on their experience. That is to say, so many pre-processes must be accomplished in order to obtain a proper configuration of midship section, which requires a lot of various knowledge like experts' experience, know-how, and their sense.

Expert system(Watermann 1986) using RBR (rule-based reasoning) always requires the generalized rules and facts to construct the knowledge-base(Yeun and Yang 1997) and to perform its deductive inference. But, it is too difficult to transform such diverse knowledge like human experience and know-how into generalized rules and facts, because it is impossible to perform the logical analysis and hierarchical decomposition about such irregular knowledge. It is often pointed out that these difficulties are crucial problems that hinder the knowledge engineers from building their own expert systems. Their efforts to overcome such a bottleneck problem of knowledge acquisition lead them to a great success by introducing CBR (case-based reasoning). CBR can infer from each actual case, so it does not require any more the generalized rules and facts. That is to say, the knowledge of CBR is a case itself. Thus, CBR can effectively encapsulate such irregular and nonlogical knowledge as it is, and efficiently reuse the knowledge as it is. Consequently, no more analysis, decomposition, and generalization about the knowledge are necessary. Though the CBR is adopted to successfully handle such irregular knowledge like human expertise and know-how, RBR is still useful in order to execute a deductive inference efficiently and effectively if there is generalized knowledge available to us. Thus, it is recommended that CBR and RBR methods are harmoniously combined in accordance with the situation of the given problem.

In this research, a hybrid method combining CBR and RBR is adopted. CBR is applied to successfully handle such irregular knowledge like human expertise and know-how and it can transform the knowledge into ready-to-use case-base effectively. Thus, the proper configuration of midship section can be obtained directly from our CBR system without such complicated and tiresome pre-processes in the early design stage. All the methods of CBR, i.e., case-organization, case-indexing, case-retrieval, case-adaptation, and case-recording are applied to our problem. Especially, our new case-adaptation methods are developed in order to obtain the configuration of midship section which satisfy the owners' requirements as perfect as possible. And, RBR is properly applied to perform the scantling of midship section based on the configuration of midship section obtained from the CBR procedure. The knowledge of DnV rules is so generalized that RBR can be applied without difficulty. Using the knowledge representation of DnV rules, RBR can carry out a deductive inference and offer the proper scantling results to us. In this way, the hybrid method can be implemented with CBR and RBR.

Our case-adaptation methods are examined by comparing the performance of our methods with the direct-mapping technology, i.e., ANN (artificial neural networks)(Haykin 1994) and GP (genetic programming)(Koza 1992). And, the RBR results are examined by considering whether the results meet the requirements of the other rules like KR and ABS or not. Finally, the reasonability of our results is also verified with regard to the current practice of shipyard by comparing the results with the actual values from parent ship.

## 2 Creating configuration of midship section using CBR

CBR(Kolodner 1993) is the problem-solving strategy. First of all, the old cases that represent previously-solved problems are stored. When new problem is given, some old cases similar to the given problem are retrieved and their solutions are applied with proper modification to solve the given problem exactly. A place where the old cases are stored is called case-base. A process that obtains old cases similar to the given problem is called case-recalling, and a process that modifies old cases to satisfy current requirements is called case-adaptation. Case-recalling process consists of two sub-processes, what is called, case-indexing and case-retrieval. In the case-indexing process, the index-attributes are identified and registered. They play a role of criterion for considering

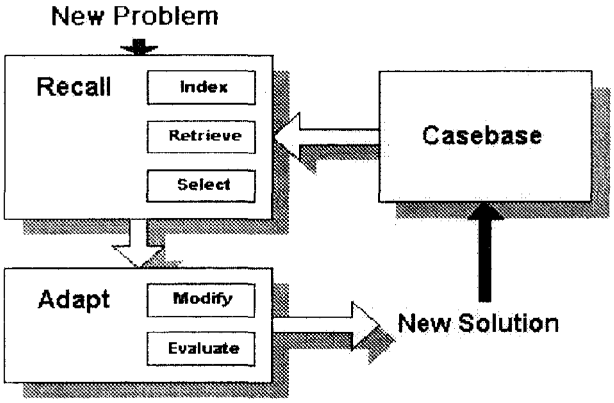


**Figure 1:** Overall structure of CBR

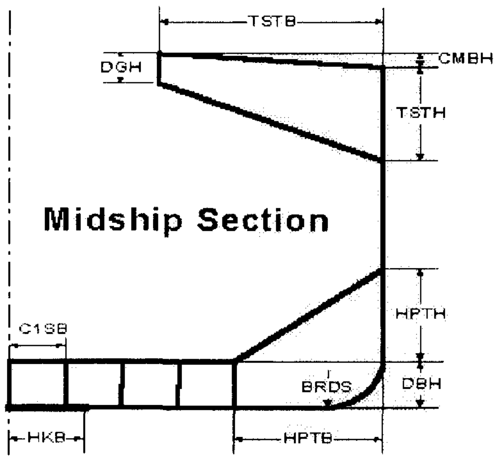


**Figure 2:** Configuration of midship section

whether the old cases are similar to the given problem. In the case-retrieval process, the case-base is searched for cases similar to the problem and some proper cases are selected as candidates for the solution to our problem. Following Figure 1 illustrates the interaction between all those processes(Maher 1995) of CBR.

## 2.1 Preparing case-base

In this research, a case is represented with the case representation method(Watson 1997) of 'requirement and solution' using the data structure of 'attribute and value', and the cases are organized into the case-base with the data structure 'linked list.' The requirement-items of a case are the owners' requirements, i.e., dead weight, speed, and draft. The solution-items of a case are the configuration components of midship section, i.e., double bottom height, bilge radius, hopper tank breadth and height, topside tank breadth and height, camber height, and so forth. These items are manifested in the following Figure 2.

## 2.2 Indexing and retrieving cases

As mentioned earlier, case-indexing process identifies index-attributes that play a role of criterion for considering whether the old cases are similar to the given problem. In this research, the attributes of owners' requirements are used as the indices of cases. And, each value of attributes is normalized to avoid over or under-estimation about the attributes and to guarantee the numerical stability. In this way, the attributes of owners' requirements can be utilized as useful indices of cases.

Basically, case-retrieval is a search process. As mentioned earlier, case-retrieval is the process in which the space of case-base is searched for the old cases similar to the given problem and finally some proper cases are selected as candidates for the solution to our problem. Thus, it is very important to accurately estimate the degree of similarity between the cases. In this research, the modified nearest neighbor algorithm(Wettschereck 1995) is used. It applies the Minkowski norm based on Euclidean distance using proper weighting factors with regard to each attribute.

## 2.3 Adapting cases

The candidates obtained from case-retrieval process cannot satisfy current requirements sufficiently, because there are always somewhat different things between current and old circumstances. Thus, the candidate-solutions cannot be applied to the problem directly but have to be fitted for the current requirements appropriately. As mentioned earlier, such a process is called case-adaptation.

Generally, the case-adaptation method can be classified into the two ways. One is a situation in that there is sufficient domain knowledge available to us and the other is a situation that is quite opposite. In the former situation, there are lots of conventional methods to apply, for example, constraint satisfaction method, parametric adaptation method, and the method in which we can build an expert system by constructing knowledge-base with the given domain knowledge. On the contrary, there are few conventional methods to apply in the latter situation, so it is often that the candidate-solutions obtained from case-retrieval are even applied directly to the given problem, which is called the method of null-adaptation. Unfortunately, the latter is dominant in our situation. Namely, so far as the configuration of midship section is concerned, there are very few applicable methods due to the lack of domain knowledge. Thus, using two different approaches, our new case-adaptation algorithms requiring no domain knowledge are developed.

### 2.3.1 Adapting cases using lazy learning

The first is a method using LL (lazy learning)(Zhang et al 1997). LL is usually compared with EL (eager learning), and the terms LL and EL explain themselves well. When the training data are given, EL performs learning process eagerly and transforms the training data into totally different one that often play a role of black-box in the mapping system. When a query is given in the future, EL makes use of not the raw training data but the black-box obtained from the learning process and generates a response corresponding to the query. ANN and GP are the typical examples of EL. During the learning process, ANN and GP transform the given training data into the networks of artificial neurons and the S-expression, i.e., parsing tree respectively. On the contrary, LL does not compile or manipulate any data previously but do nothing until the query is given. This is the reason why LL is lazy. Only when a query is given in the future, LL executes learning process

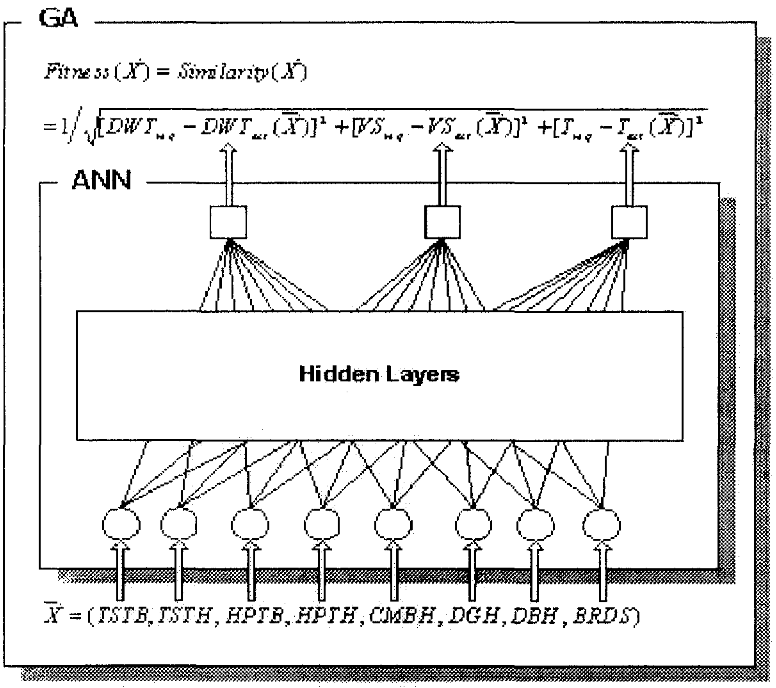


**Figure 3:** Case-Adaptation algorithm using GA and ANN

in which LL uses some of given training data and proper approximation tools and generates a response corresponding to the query.

In this research, the LL using locally weighted linear regression is applied. When a query is given, some local instances close to the given query are retrieved from the training data. Then, each distance between the query and the instances is calculated. And, each weighting factors according to the each distance is also calculated using proper kernel function. In succession, the weighted-summation is performed with the each weighting factor and the local instances, and finally a response corresponding to the query is generated. In this way, the adapted case can be obtained with some retrieved cases.

### 2.3.2 Adapting cases using GA and ANN

The second method makes use of GA(Goldberg 1989) and ANN(Yeun et al 1997) and it can be shown as following Figure 3.

It is supposed that ANN implemented in this research have too many input dimensions to execute learning process successfully, so the dimensional reduction technique based on principal component theory is also implemented in the ANN algorithm. Anyway, the case-adaptation algorithm can be described in detail as follows.

1. Prepare the requirement-functions of the solution-vector $\chi$, i.e., DWT($\chi$), VS($\chi$), and T($\chi$) by implementing inverse mappings from the solution space to the requirement space using ANNs. The solution-vector $\chi$ equals the vector form of the solution-attributes, i.e., $\chi$ = (TSTB, TSTH, ... , DBH, BRDS).

2. Make the solution-vector $\chi$ correspond to the phenotype of an individual, i.e., the design variable of optimization process and its binary code correspond to the genotype of the individual.

3. Generate initial population with individuals that have the solution values of the retrieved cases from case-retrieval process.

   3-1. Using the requirement-functions DWT($\chi$), VS($\chi$), and T($\chi$), calculate current requirement values DWT, VS, and T corresponding to solution-vector $\chi$ of current individual.

   3-2. Calculate Euclidean distance between the current requirement values of the individual and the constant requirement values from owners, and obtain the degree of similarity by calculating the reciprocal value of the distance which means an objective of optimization process. The degree of similarity means the degree of owners' satisfaction about the current individual.

   3-3. Take the degree of similarity as a fitness of current individual.

   3-4. Apply the procedures 3-1, 3-2, and 3-3 to all the individuals in the population.

4. Perform selection process.

5. Reproduce new population by performing crossover and mutation process with the selected individuals.

6. Apply the procedures 3-1, 3-2, 3-3, and 3-4 to the new population.

7. Repeat the procedures 4, 5 and 6 until the objective value is sufficiently small or iteration counter reaches maximum number

In brief, our case-adaptation algorithm can be embodied by evolving the individuals of midship section configuration into fitter individuals and selecting the fittest individual among those individuals with regard to the satisfaction of owners' requirements.

## 3 Midship section scantling using RBR

As mentioned earlier, RBR is applied in order to obtain the scantling of midship section. If there is a generalized knowledge about the given problem domain, RBR can perform an intelligent inference which replicates a deductive thinking process of human beings. As for the scantling of midship section, there is knowledge called the rules of DnV which is generalized enough to apply RBR. Thus if RBR is applied to our current problem, RBR can perform an inference effectively in order to determine which component of midship section must be considered, and how much it must be modified when the midship section modulus does not meet the requirement of DnV rules. In this research, knowledge-base is constructed using the conventional method of knowledge representation containing the representation of Rule and Fact. Unit Rule is represented with the data structure of Condition-Hypothesis-Action and Unit Fact is represented with the object-oriented data structure based on fame and class. As for the method of inference, forward and backward chaining methods are applied.

**Table 1:** Comparison of results - creating configuration of midship section

| | Direct Mapping | | | | CBR | | | | Parent Ship |
|---|---|---|---|---|---|---|---|---|---|
| | ANN | | GP | | LL | | GA and ANN | | |
| | Value(m) | Error(%) | Value(m) | Error(%) | Value(m) | Error(%) | Value(m) | Error(%) | Value(m) |
| DWT | No Meaning | | No Meaning | | 71091.91 | 2.2120 | 72689.30 | 0.0147 | 72700.0 |
| VS | | | | | 13.98 | 3.5855 | 14.59 | 0.6241 | 14.5000 |
| T | | | | | 13.62 | 1.9919 | 13.88 | 0.1101 | 13.8960 |
| TSTB | 8.91 | 1.8281 | 9.12 | 0.5003 | 8.90 | 1.9096 | 9.08 | 0.0353 | 9.0750 |
| TSTH | 5.46 | 2.0729 | 5.21 | 2.6112 | 5.19 | 2.9757 | 5.36 | 0.2131 | 5.3500 |
| HPTB | 4.50 | 1.6072 | 4.49 | 1.3725 | 4.41 | 0.4718 | 4.42 | 0.2167 | 4.4300 |
| HPTH | 4.30 | 2.4881 | 4.31 | 2.6405 | 4.31 | 2.6048 | 4.19 | 0.2190 | 4.2000 |
| CMBH | 0.58 | 3.2167 | 0.58 | 3.2333 | 0.63 | 5.0833 | 0.60 | 0.5500 | 0.6000 |
| DGH | 0.62 | 3.4333 | 0.62 | 3.3667 | 0.58 | 3.2833 | 0.61 | 2.0167 | 0.6000 |
| DBH | 1.71 | 5.0333 | 1.89 | 5.0389 | 1.89 | 5.0222 | 1.81 | 0.5722 | 1.8000 |
| BRDS | 1.84 | 2.2389 | 1.85 | 2.9500 | 1.85 | 2.6444 | 1.80 | 0.1444 | 1.8000 |
| Average | | 2.7398 | | 2.7142 | | 2.8895 | | 0.4288 | |

## 4 Results and comparison

Our case-base is organized with 77 cases which contain the information about the configuration of midship section from actual parent ships, and it is assumed that the owner give us their requirement values of dead weight, speed, and draft as 72700 ton, 14.5 knot, and 13.896 m respectively. Three cases of top-three degree of similarity are retrieved. And the cases are adapted using lazy learning and genetic algorithm respectively. Direct mapping from the requirement space to the solution space is also performed using ANN and GP in the same condition as CBR. As for the ANN, its hidden layers are optimized using GA in order to maximize its learning capability. Finally, our CBR result is compared with ANN and GP, and the reasonability of the result is verified with respect to the current practice of shipyard. The results and comparison can be manifested as Table 1 in which actual values from the parent ship are used for attributes HKB and C1SB. As can be seen in Table 1, it turns out that all the methods can make quite satisfactory results in which the average values of errors are smaller than 3%. And, the method of CBR using GA and ANN produces the best result in which the average error value is only 0.43%. It is remarkable that the method of CBR using LL produces pretty good result in spite of its short computing time. For the values of DWT, VS, and T in the ANN and GP column in Table 1, since direct mapping algorithm just uses the values of owners' requirements as queries, there can be only the values of response-errors. Thus, the errors of owners' requirements have no meaning.

The rules of DnV are applied to construct the knowledge-base of expert system and the inference is executed to perform the scantling of midship section using forward and backward chaining properly. As can be seen in Table 2, all the values of structural components are meet the requirements of not only current DnV rules but also the other rules like KR and ABS. And, it can be seen that the results of RBR are not optimal but just feasible. That is to say, the results of RBR may be effectively used as an initial design point of the optimization process in the future. Thus, if the optimization may be performed with the results of RBR, the fined-tuned scantling results can be

**Table 2:** Comparison of results - scantling of midship section

| Area : $m^3$ Thickness : $m^3$ | Scantling | Parent Ship | Minimum | |
|---|---|---|---|---|
| | | | KR | ABS |
| Keel | 19.5 | 17 | 17 | 17 |
| Outer Bottom | 19.5 | 15 | 15 | 16 |
| Inner Bottom | 20.5 | 18 | 17 | 15.5 |
| Bilge | 21 | 18.5 | 17 | 16.5 |
| Center Girder | 18.5 | 16 | 15 | 15 |
| Side Girder 1 | 18.5 | 16 | 12 | 12 |
| Side Girder 2 | 15 | 12.5 | 12 | 12 |
| Side Girder 3 | 14 | 11.5 | 11.5 | 12 |
| Side Girder 4 | 14 | 11.5 | 11.5 | 11.5 |
| Hopper Side Shell | 21 | 18.5 | 16.5 | 15.5 |
| Middle Side Shell | 21 | 18.5 | 16 | 15.5 |
| Topside Side Shell | 21 | 18.5 | 16 | 15 |
| Upper Deck | 21 | 18.5 | 16.5 | 16 |
| Deck Girder | 21 | 19.5 | 15 | 14.5 |
| Hopper Bulkhead | 22.5 | 20 | 16 | 15.5 |
| Topside Bulkhead | 21 | 18.5 | 16 | 17 |
| Midship Section Area | 3.873 | 3.409 | | |

obtained and it may be possible that better results than parent ship can be obtained. Such a hybrid system of case-based reasoning, rule-based reasoning and optimization is our next research target.

## 5 Conclusion

In this research, hybrid system of CBR and RBR was developed. Especially, our own case-adaptation methods not requiring any domain knowledge were developed and applied to our problem, i.e., creating the configuration of midship section. The methods could be applied easily and produce pretty good results. And, the scantling of midship section is performed efficiently using RBR. Finally, our methods were compared with other traditional methods and also verified with respect to current practice.

As a result, the following two remarks can be concluded. Firstly, CBR system with our case-adaptation methods can effectively support so many tiresome jobs which require a lot of irregular knowledge like human expertise in order to get the proper configuration of midship section in the earlier design stage. Secondly, the scantling process can be efficiently executed using RBR and it can produce good initial design of next optimization process. In the future, the hybrid system of CBR, RBR and optimization can complete the structural midship section design.

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