

A novel adaptation approach for electromagnetic device optimization*

JUN OUYANG, DAVID LOWTHER

*Department of Electrical and Computer Engineering, McGill University
3480 University Street, Montreal, H3A 2A7, Canada
e-mail: {jun.ouyang/david.lowther}@mail.mcgill.ca*

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Abstract: The ability of case-based reasoning systems to solve new problems mainly depends on their case adaptation knowledge and adaptation strategies. In order to carry out a successful case adaptation in our case-based reasoning system for a low frequency electromagnetic device design, we make use of semantic networks to organize related domain knowledge, and then construct a rule-based inference system which is based on the network. Furthermore, based on the inference system, a novel adaptation algorithm is proposed to derive a new device case from a real-world induction motor case-base with high dimensionality.

Key words: case-based reasoning, case adaptation, semantic networks, electromagnetic (EM) devices, optimization

1. Introduction

Case-based reasoning (CBR), an approach to using past experiences to solve new problems, is a compelling approach to the design of an EM device. Assuming that similar problems have similar solutions, the design process often starts with retrieving the most similar device case(s) from the current case base, then modifying the retrieved ones to fit the new situation. The process of adjusting the previous solution is called case adaptation and related to optimization. The complexity of an adaptation process depends on the practical problem itself. So far, there are no generally available approaches for case adaptation [1]. In our CBR-based system for EM device design, we adopt semantic networks to represent knowledge from electromagnetics, and then extract inference rules from the networks. These rules function as a reasoning tool to guide the process of deriving a new solution for a given design task. A semantic network is defined as a graphical structure containing patterns of interconnected nodes and arcs in which the nodes stand for concepts and the arcs indicate the relationships among concepts [2]. As an extension of the paper in [3], this paper will review different case adaptation methods used in CBR systems, and then describe how to employ a semantic network approach to carry out a novel case adaptation strategy for EM device design.

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2. Related work

2.1. Traditional case adaptation strategies

In this Section, three kinds of widely used case adaptation methods are introduced.

1) *Reinstantiation*

When facing a situation in which the retrieved case perfectly matches the given problem, it can be adopted as the solution.

2) *Substitution*

In this method, certain parts of the case retrieved are replaced because these parts are not valid when dealing with a new problem. Domain knowledge is required to guide a proper substitution process. This case adaptation method has been used in a wide range of practical CBR systems, such as ISAC (a CBR System for Aircraft Conflict Resolution) [4], SCINA (the interpretation of myocardial perfusion scintigrams) [5], a two layer medical image understanding system [6], Breathalyser (a web-based CBR application for predicting blood alcohol content) [7], Neuropathy Diagnosis (a CBR system for the study of neuromuscular diseases) [8], and Truth-Teller (a program comparing pairs of cases presenting ethical dilemmas about whether to tell the truth) [9].

3) *Transformation*

When there is no appropriate substitute available, it is needed to adjust the structure of the solution part of the case retrieved. Domain knowledge is used to guide how to make appropriate changes in order to derive a solution. The following CBR systems adopted transformation adaptation strategies: CARMA (a case-based range management advisor system) [10], SaxEX (a case-based reasoning system for generating expressive musical performance) [11] and RESYN/CBR (a case-based planning system for organic synthesis) [12].

2.2. Recently developed case adaptation methods

Recently, new approaches have been developed to extend the adaptation ability of CBR systems. Typical of these are hybrid methods (such as integrating rule-based reasoning into a CBR system) and learning based adaptation approaches (i.e. applying machine learning techniques to derive adaptation knowledge).

1) *Hybrid adaptation approaches*

In [13], Leake et al. apply a hybrid mechanism, a combination of rule-based and CBR, to implement case adaptation. The rules are obtained by interviewing domain experts and used to derive a solution to a problem at hand. If no rules are appropriate for a presented problem, then a case-based adaptation module is triggered to search for an adaptation case which describes previous successful adaptation steps to a similar old problem.

2) *Case adaptation using a machine learning method*

Machine learning approaches have been used to automatically acquire adaptation knowledge when a situation exists in which researchers can obtain a large enough number of case instances

(examples). Frequently used learning techniques to train a learning model include fuzzy decision trees, neural networks, Bayesian models, support vector machines (SVM), etc. [14].

3. Case adaptation for EM devices

Since there are a limited number of EM devices cases in hand, we need to adopt a new approach to building an adaptation module for our case-based design system. In this Section, we build a two-level semantic network to represent the global and local relations between the sub-components of an EM device, and then use this to construct a rule-based inference system. A network for an induction motor is chosen as an example to illustrate the operational details of an adaptation process. All the rules are coded as an inference knowledge base in the Java Expert System Shell (JESS), a rule engine for the Java platform [15].

3.1. A semantic network-based adaptation module

1) *The reason for using semantic networks*

As a formal knowledge representation and organization method, a semantic network possesses the following salient advantages [16].

- a) It provides explicit and succinct descriptions of structures.
- b) It reduces the complexity of searching and thus speeds up the adaptation process.
- c) It describes domain knowledge very effectively.

2) *The process of constructing semantic networks*

Conceptually, a device's features form a semantic network whose nodes represent device components or their performance attributes; while network links describe the relations amongst them. These networks provide adaptation knowledge which is hidden in a case base. Two-level semantic networks are adopted to explicitly represent adaptation knowledge. The first level, which is based on lumped circuits, is able to illustrate the global semantic relations within an electromagnetic device; the second level depicts the local relations and material properties within critical device components. The equations from Hubert's textbook [17] and Bouffard's lecture notes [18] are used to create the semantic network structure, and then the network is employed to derive the rules.

3) *An example: semantic networks for a three phase induction motor*

Figure 1 (the global relations among device features) and Figure 2 (a part of local relations within device components) comprise a two-level semantic network of a three phase induction motor. The parameters which strongly influence the behaviour of a motor (such as, Pmech, TD, Vs and Ir, etc.) and the geometrical structure of a motor (g, Sl and Dag) are crucial.

The related parameters in Figure 1 and Figure 2 are listed in Table 1. Here, the symbol “+” indicates that the value on the head side increases when there is an increase on the tail side; the “-” denotes that the value on the head side decreases when there is an increase on the tail side, i.e. an inverse relationship.

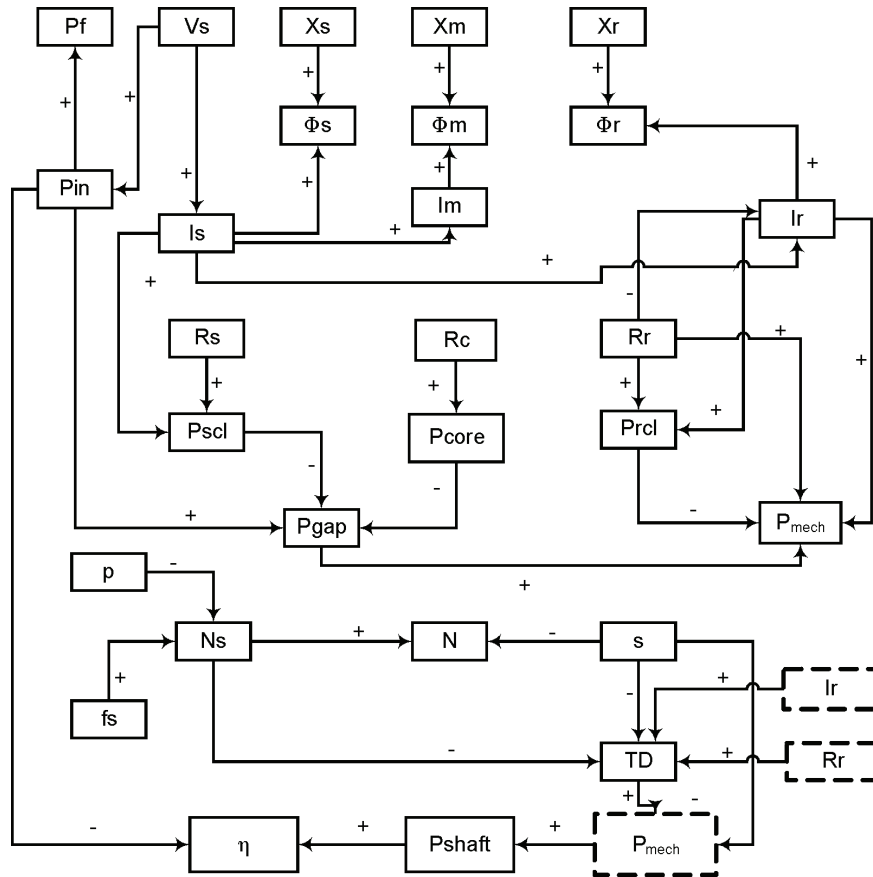


Fig. 1. A semantic network theory of an induction motor at the circuit level [17]

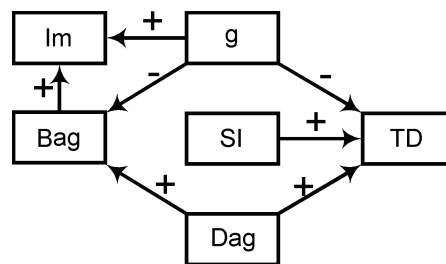


Fig. 2. A part of the local relations of an induction motor [18]

4) A rule-based inference system

Using the networks in Figure 1 and Figure 2, a rule-based inference system has been built. Each network link corresponds to a rule and several typical inference rules are presented in Figure 3. In total, 44 rules have been extracted from the semantic networks.

Table 1. The parameters for induction motor semantic networks

Symbol	Meaning	Symbol	Meaning
Pf	power factor	Is	stator current
Vs	stator volt	Im	magnetizing current
Xs	stator reactance	Ir	rotor current
Pin	input power	Rs	stator resistance
Xm	magnetizing reactance	Φ_s	leakage flux for the stator
Xr	rotor reactance	Rc	resistances for the core loss
Φ_m	magnetizing flux	Rr	rotor resistance
Psc1	stator conductor loss	Prcl	rotor conductor loss
Pmech	mechanical power	Pgap	the net power crossing the air gap
p	pole numbers	fs	frequency
Ns	synchronous speed	N	mechanical speed
TD	developed torque	η	efficiency
Pshaft	shaft power	s	Slip
Sl	stack length	Bag	B-field in the air gap
Dag	the diameter of g	g	air gap length
Φ_r	leakage flux for the rotor	Hp	horse power

If there is an increase in mechanical speed (N_r), developed torque (TD) or rotor resistance referred to the stator (R_r), then the mechanical power (P_{mech}) will increase.

If there is an increase in stack length (Sl) or a decrease in air gap length (g), then the developed torque (TD) will increase.

If there is a decrease in air gap length (g), then the magnetic field in the air gap (Bag) will increase.

Fig. 3. Three typical rules for induction motor optimization

3.2. A novel multi-objective optimization algorithm for EM device adaptation

In the following, we describe the design of a novel algorithm for EM device optimization in detail. A three phase induction motor is chosen as a test example to introduce the operational aspects of an adaptation process in our CBR system.

We designed a novel adaptation algorithm (shown in Fig. 4) to solve a multi-objective optimization problem for an induction motor. While the design is intended to handle multiple objectives, to simplify the process, all of the objective functions have been combined into a single functional form, i.e. a weighted linear sum of the objectives [19]. The rule-based inference system is able to derive information on the direction of change of related design

parameters in the design space, and past design experience is used to set up the initial value of a change rate to start an optimization process.

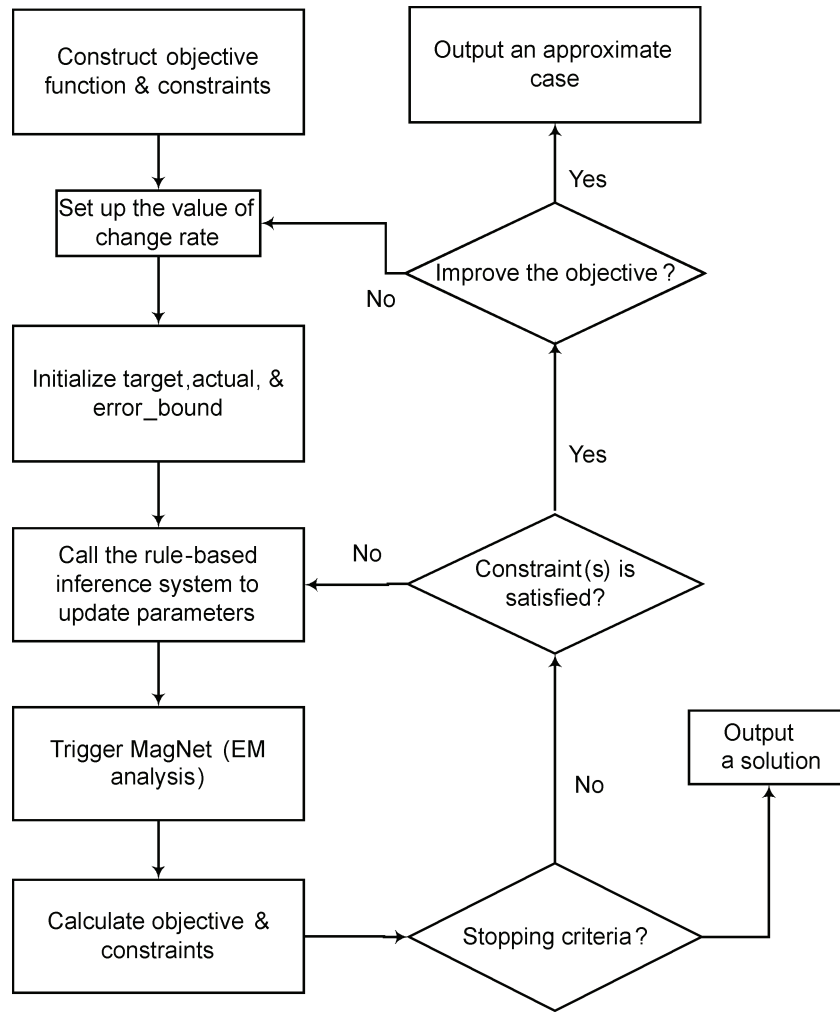


Fig. 4. The framework of a novel case adaptation algorithm for an EM device optimization

The algorithm includes the following steps:

- 1) Constructing the objective function and constraints:

$$\text{target} = \sum_{i=1}^n w_i(\text{feature}_i(i)), \quad (1)$$

$$\text{actual} = \sum_{i=1}^n w_i (\text{feature}_a(i)), \quad (2)$$

$$\text{error_bound} = \text{abs}(\text{target} - \text{initial_actual}), \quad (3)$$

$$\text{objective} = \text{relative_error} = \text{abs}\left(\frac{\text{target} - \text{actual}}{\text{error_bound}}\right), \quad (4)$$

$$\text{constraint}_i: \text{abs}\left(\frac{\text{feature}_t(i) - \text{feature}_a(i)}{\text{feature}_t(i)}\right) \leq \text{bound}(i). \quad (5)$$

Here, $\text{feature}_t(i)$ denotes the i th feature of the desired target device and $\text{feature}_a(i)$ indicates the i -th feature of an actual case; $\text{abs}(\)$ represents a function used to calculate the absolute value of $(\)$ and w_i is a weighted value corresponding to the i -th feature.

The error_bound (Eq. 3) is defined as the difference between the target and the initial value of the actual parameter or feature (represented as initial_actual).

The objective function or relative_error is defined in Equation 4.

The constraints are defined in Equation 5, in which $\text{bound}(i)$ represents the design boundary, i.e. the limits on the parameter.

2) Updating related design parameters: the inference engine (Section 3) is able to derive the facts describing in which direction the related design parameters should be changed in the design space in order to move towards an optimal solution.

3) Triggering an electromagnetic analysis (using MagNet [20]) to test the performance of a derived candidate EM device.

4) Setting the stopping criteria: the given boundary of relative_error is attained or the maximum number of iterations is reached.

Past successful experiences are employed to set up the initial value of the change rate.

4. Empirical study

The adaptation algorithm described above has been implemented in our case-based design system to solve a two-objective (N and Hp) optimization problem for an induction motor (Figs. 5 and 6).

According to the principle proposed in Section 3, in this experiment we combine two target features (N and Hp) into a single functional form: a weighted linear sum of the objectives.

For instance, to design an induction motor with a rated power of 26 hp and rated speed of 3500 rpm, our CBR system sorts the induction motor case base based on the parameters, horse power and mechanical speed and then searches for similar cases. The case with 14.45 hp and 2979 rpm has been selected from the case base to launch an adaptation process since it has

parameters (rated horse power and mechanical speed) which are closest to the design requirements.

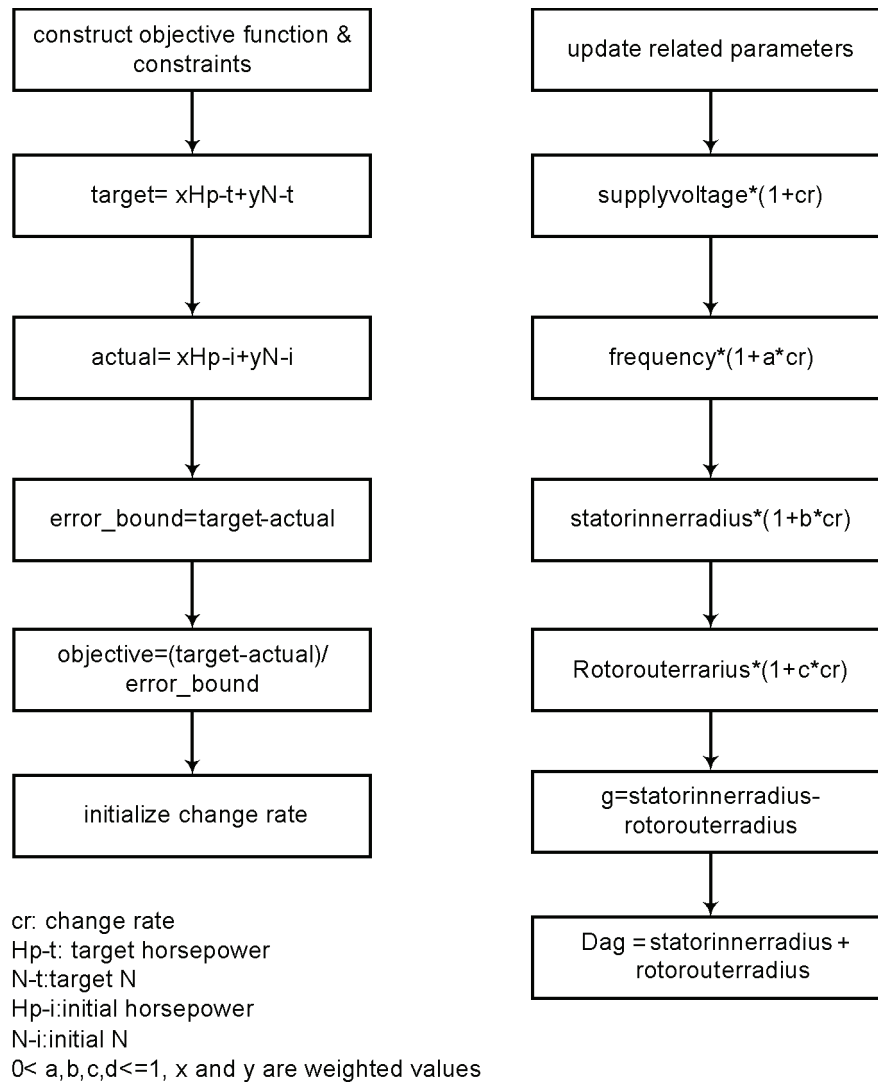


Fig. 5. The first part of an adaptation algorithm for a three phase induction motor optimization

4.1. Experimental results

The detailed convergence of the variable parameters (VS, Sl, Dag, g, slip, fs and poles) is shown in Table 2. The detailed information about the optimization processes of the two target features (N and Hp) and the objective are shown in Figures 7-9, respectively. The entries from case (1) to case (6) (Table 2) correspond to Adaptation step(s) in Figures 7-9, respectively.

For this particular task, the initial value of change rate (cr) is 0.1; the weighted value for N is 3340; the weighted value for Hp is 1; the given boundary of relative_error is 0.12; the maximum number of iterations is 12; the bound1 for constraint1 is set as 0.1; the bound2 for constraint2 is 0.02.

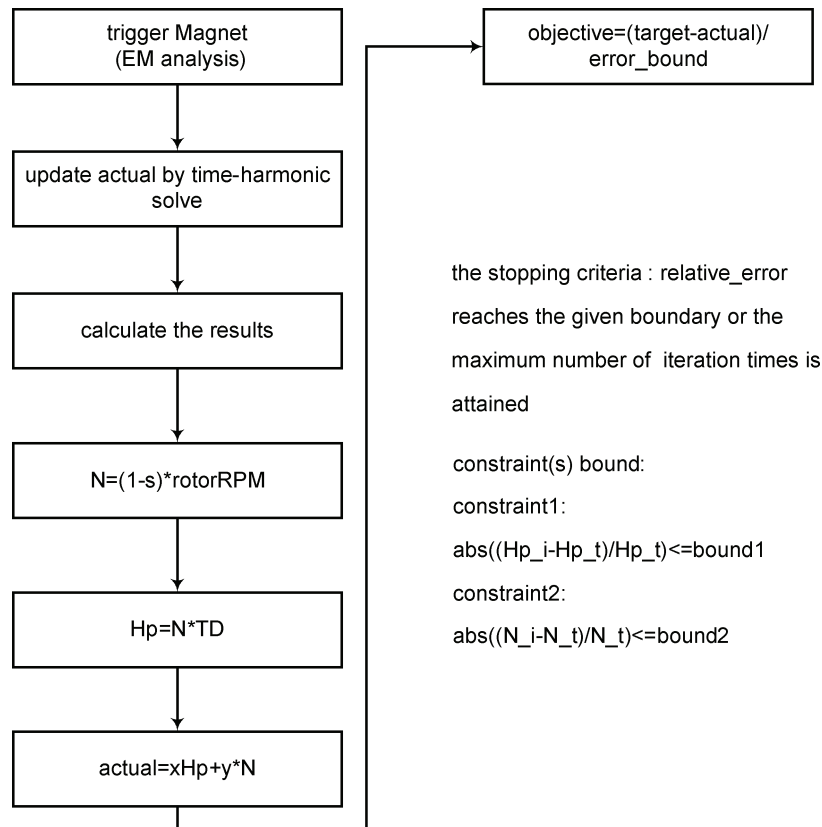


Fig. 6. The second part an adaptation algorithm for a three phase induction motor optimization

Finally, the derived case (6) with 25.5 hp and 3517 rpm is chosen as an approximate solution.

Table 2. The convergence process for fine-tuned parameters

Feature	Vs (v)	Sl (mm)	Dag (mm)	g (mm)	slip	f _s (Hz)	p
case(1)	4200	220	115.233	0.9	0.05	52	2
case(2)	4620	231	115.248	0.855	0.04975	55	2
case(3)	4989.6	240	115.263	0.81	0.049551	57	2
case(4)	5308.9	248	115.278	0.765	0.049392	59	2
case(5)	5580.8	254	115.293	0.72	0.049266	60	2
case(6)	5809.3	259	115.308	0.675	0.049165	62	2

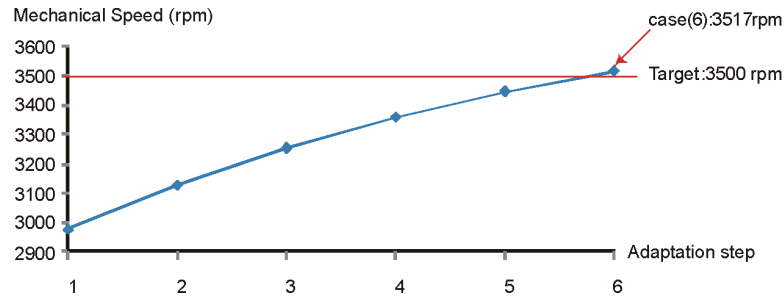


Fig. 7. The convergence process of N

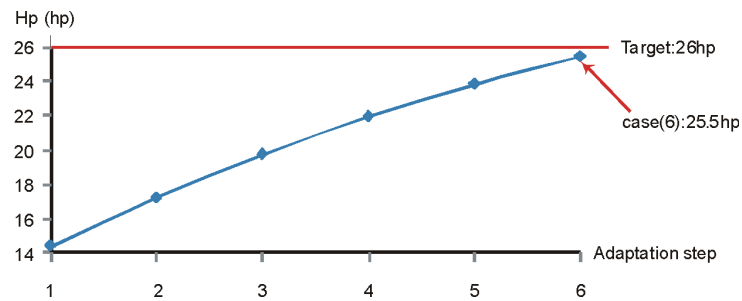


Fig. 8. The convergence process of Hp

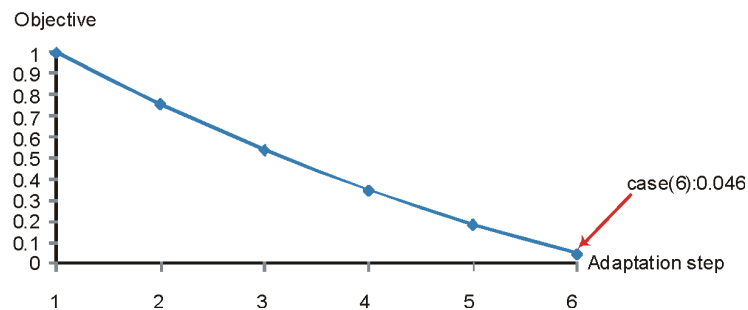


Fig. 9. The convergence of the objective

5. Conclusion

A rule-based inference system based on the concept of semantic networks has been built. Also, a novel adaptation algorithm has been designed and implemented to solve an induction motor design problem. In effect, the rule-based adaptation method provides an efficient and fast method for exploring the potential design space allowing the optimizer to concentrate on the exploitation phase. The experimental results demonstrate the practical significance and effectiveness of the adaptation strategy presented in this paper.

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References

- [1] Kolodner J., *Case-based reasoning*. Morgan Kaufmann: San Mateo, CA (1993).
- [2] Sowa J.F., *Semantic nNetworks*. [in:] Shapiro S.C. (ed.), *Encyclopedia of artificial intelligence*. 2nd edition, New York: John Wiley, pp. 1493-1511 (1992).
- [3] Ouyang J., Lowther D., *The use of semantic networks to adapt a design prototype for electromagnetic device optimization*. 14th Biennial IEEE Conference on EM Field Computation, Chicago, USA (2010).
- [4] Bonzano A., *ISAC: A case-based reasoning system for aircraft conflict resolution*. Ph.D. Thesis, University of Dublin (1998).
- [5] Haddad M., Moertl D., Porenta G., *SCINA: A case-based reasoning system for the interpretation of myocardial perfusion scintigrams*. Proc Computers in Cardiology 761-764 (1995).
- [6] Grimnes M., Aamodt A., *A two layer case-based reasoning architecture for medical image understanding*. Advances in Case-Based Reasoning 164-178 (1996).
- [7] Doyle M., *Web-based CBR in Java, final year project*. Ph. D. thesis, Trinity College Dublin, (1997).
- [8] Malek M., Rialle V., *Design of a case-based reasoning system applied to neuropathy diagnosis*. Advances in Case-Based Reasoning 255-265 (1995).
- [9] Ashley K., McLaren B., *Reasoning with reasons in case-based comparisons*. Case-Based Reasoning Research and Development 133-144 (1995).
- [10] Hastings J., *Global and case-specific model-based adaptation*. Proc AAAI Fall Symposium on Adaptation of knowledge for Reuse (1995).
- [11] Arcos J., de Mantaras R., Serra X., *Saxex: a case-based reasoning system for generating expressive musical performances*. Journal of New Music Research 27: 194-210 (1998).
- [12] Lieber J., Napoli A., *Adaptation of synthesis plans in organic chemistry*. Proc Workshop Adaptation in Case-Based reasoning (ECAI) (1996).
- [13] Leake D., Kinley A., Wilson D., *Acquiring case adaptation knowledge: a hybrid approach*. AAAI Proceedings 684-689 (1996).
- [14] Pal S.K., Shiu S.C.K., *Foundations of soft case-based reasoning*. Morgan Kaufmann: Wiley, (2004).
- [15] Jess 7.0p1, *The rule Engine for the JavaTM Platform*. Ernest Friedman-Hill, Sandia National Laboratories, CA (2008).
- [16] Lowther D., *ECSE 549: expert systems in electrical design*. Lecture Notes, McGill University, (2011).
- [17] Hubert C.I., *Electric machines: theory, operation, applications, adjustment, and controls*. Merrill, Columbus, OH. (1991).
- [18] Bouffard F., *ECSE 361: power engineering*. Lecture Notes, McGill University (2011).
- [19] Marler R.T., Arora J.S., *Survey of multi-objective optimization methods for engineering*. Structural and multidisciplinary optimization 26: 369-395 (2004).
- [20] *MagNet Users manual*. Infolytica Corporation, Montreal, Canada (2011).