# Genetic Optimization of a Fuzzy System for Charging Batteries

**Hartmut Surmann**

*Abstract*— **A large variety of Nickel Cadmium (NiCd) batteries have been developed to meet a wide range of user needs, ranging from low current level applications like emergency power sources for semiconductor memories to very high power applications such as motor-operated cordless drills. This paper presents a genetic algorithm approach to optimize a fuzzy rule-based system for charging high power NiCd batteries. For the optimization of the fuzzy system a special objective function is developed which is based on the entropy of a fuzzy system. The resulting fuzzy system is able to charge high power NiCd batteries in about 10 minutes with a current of 6A.**

*Keywords*— **Genetic algorithm, fuzzy rule-based systems, high current battery charger, fuzzy rule-base entropy.**

## I. Introduction

A fuzzy rule-based system (FRBS) describes the $n$-dimensional state space through the formulation of hypotheses in the form of fuzzy rules over the linguistic variables and their linguistic labeled membership functions. The FRBS implements a partial, $n$-dimensional function $f : U \subset \mathbb{R}^n \to \mathbb{R}$ over a compact set $U$.

Incorporating inexact reasoning into usable form can present problems of imprecision or uncertainty. Fuzzy theory addresses such problems by attaching measures of credibility to propositions. Mamdani's work [1] on fuzzy control, which was motivated by Zadeh's approach to inexact reasoning [2], led many researchers to work in this field. The basic idea of this approach was to incorporate the know-how of a skilled human operator into fuzzy sets and fuzzy rules, which would then be combined by the fuzzy implication and the compositional rule of inference.

The difficulty with compiling the control know-how may be due to the nonlinear, time-varying behavior of the system or the poor quality of available measurements. To mirror natural language concepts, fuzzy logic replaces true and false with continuous membership values ranging from zero to one. This allows the processing of linguistic concepts (adjectives, adverbs) like "small", "big", "near", or "approximately" in the control system. The main advantage is to control processes that are too complex to be mathematically modeled in real time.

The fuzzy knowledge base is normally either acquired from a human expert or from a referential data set with neural or genetic algorithms [3]. On one hand, the input/output behavior is relatively easy to describe and maintain. On the other hand, the automatic design or optimization of such system is aggravated through the $k \times l \times n \times m$ degrees of freedom, where $n = \#$ input variables, $m = \#$ output variables, $k = \#$ membership functions, and $l = \#$ fuzzy rules.

In 1989, Karr et al. introduce the optimization of fuzzy systems with a genetic algorithm (GA) [4]. While genetic algorithms don't make special assumptions on the I/O space, they are useful to optimize high dimensional problems [5] and thus be used for complex fuzzy systems. Besides the change of the position [4] and width [3] of the membership function, it is also possible to optimize the fuzzy rules [6] or fuzzy operators.

Before we discuss the GA approach in section four, a formal, brief overview of fuzzy control theory and the recharge process of NiCd batteries is given. An extended introduction to FRBS can be found in many good textbooks, e.g., [7], [8], and to battery operations in [9], [10].

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## II. Basic terms of FRBS

The fuzzy rule-based algorithm is based on the generalized modus ponens inference rule [11]:

| | |
|---|---|
| Premise: | A is true |
| Implication: | If A then B |
| Conclusion: | B is true |

Fuzzy functions then replace "crisp" propositions A and B. These functions characterize and define fuzzy sets $U$ through $\mu_i : U \to [0,1]$ with $x \mapsto \mu_i(x)$, so $i = \{(x, \mu_i(x)) | x \in U, \mu_i(x)\}$. Zadeh [2] defines for $x \in U$ three important operations for fuzzy sets:

$$\text{Intersection } C = A \cap B,$$
$$\mu_C(x) = \min(\mu_A(x), \mu_B(x))$$
$$\text{Union } C = A \cup B,$$
$$\mu_C(x) = \max(\mu_A(x), \mu_B(x))$$
$$\text{Complement } \bar{A},$$
$$\mu_{\bar{A}}(x) = 1 - \mu_A(x)$$

$A$, $B$ and $C$ are fuzzy sets and $U$ is the universe of discourse for $x$. These fundamental operations together with the set [0,1] form a fuzzy algebra, so that any logic function can be built. After Zadeh's basic work a lot of other fuzzy operations have been defined [12], [13]. The important operations fulfill the triangular norm (t-norm, e.g., minimum) or t-co-norm (e.g., maximum) conditions. Instead of $\mu_A(x)$ we only write A to denote the fuzzy set A. Replacing continuous functions with unit pulses implements the Boolean algebra, subset of the fuzzy algebra. In contrast to a conventional knowledge-based system, the premise of the rule is a value in [0,1] instead of {0,1}. The example in Fig. 1

introduces the basic fuzzy algorithm. It shows three simple rules for the battery charger with two inputs ($n = 2$) dU (gradient of voltage), T (temperature) and one output ($m = 1$) I (current).

R1: IF dU is high and T is normal
THEN I is four
R2: IF dU is small and T is normal
THEN I is two
R3: IF dU is small and T is normal
THEN I is four

Fuzzified inputs dU and T are simultaneously switched to all the rules to be compared with the stored premises (IF parts). Now the truth values $\alpha_i^{dU}$, $\alpha_i^T$ for every subpremise are calculated by:

$$\begin{aligned} \alpha_i^{dU} &= \mu_{A_i}(dU) \quad , for\ A_i \in \{s., m., h.\} \\ \alpha_i^{T} &= \mu_{B_i}(T) \quad , for\ B_i \in \{normal\} \\ & \quad , for\ i = 1 \dots 3 \end{aligned} \tag{1}$$

$\alpha_1^{dU} = 0.0$ indicates that the input completely mismatches with the stored subpremise, which leads to a complete noncontribution of rule 1 to the output. $\alpha_2^{dU} = 0.2$ and $\alpha_1^T = 0.55$ in rule 2 generates a rule matching or truth value of $\omega_i = 0.2$, because the fuzzy logic conjunction "and" is interpreted as the minimum of $\alpha_i^{dU}$ and $\alpha_i^T$ ($\omega_i = \min(\alpha_i^{dU}, \alpha_i^T)$). The conclusion of each rule is

$$I_i' = \{\min(\omega_i, I_i(x)) \mid x \in I_i\}, \quad \text{for } i = 1 \dots 3 \tag{2}$$

and represents the conclusion (THEN part) of each rule.

Now, we calculate the fuzzy result function $I'$, which is the unification of all sub results $I_i'$, as follows:

$$I' = \bigcup I_i', \text{ for } i = 1 \dots 3^1. \tag{3}$$

In most applications the output values are "crisp" numbers (unit pulses), which are accomplished by calculating the center of gravity (COG) of the resulting fuzzy function $I'$:

$$COG_I = \frac{\int x \times I'(x)dx}{\int I'(x)dx} \tag{4}$$

The described FRBS with binary input and output values is called BIOFAM (Binary Input-Output Fuzzy Associative Memory) [7] or the MIN-MAX algorithm [1] with the COG used as defuzzification method.

The calculation of the fuzzy result function $I'$ and the center of gravity are the bottleneck during the computation of the fuzzy algorithm. Therefore, a modified result function calculation (FCOG) [14] is suggested, in which the center of area $M_i$ and the area $A_i$ of a membership function are calculated before run time (q = number of output membership functions):

$$\begin{aligned} A_i = \int I_i(x)\ dx, \quad M_i = \int x \times I_i(x) dx \\ COG_I = \frac{\sum_{i=1}^{l} \omega_i \times M_i}{\sum_{i=1}^{q} \omega_i \times A_i} \end{aligned} \tag{5}$$

[1] compositional rule of inference [1]

A FRBS with multiple inputs and one output is called a MISO fuzzy rule-rule based system. Each multiple input/multiple output (MIMO) FRBS with $m$ output variables is a unification of several MISO systems. MIMO describes a partial, n-dimensional, nonlinear and dynamic free function $f : U \subseteq I\!R^n \rightarrow I\!R^m$, because the I/O behavior of the FRBS depends only on the current input vector and the algorithm has no storing or delaying elements.

More mathematically the 6-tuple FRBS = ($\mu_{ab}$,$R$,$T$, $I$,$T - CO$,$DEF$) is a family of fuzzy systems FS. It has membership functions $\mu$, the fuzzy rule base $R$, the t-norm fuzzy conjunction $T$, the implication $I$ verifying $I(a, 0) = 0$ $if\ a \neq 0$ (e.g., an R-implication or t-norm), the t-co-norm T-CO and the defuzzification method DEF (e.g., center of gravity, maximum or FCOG). The main parameters for the FRBS are the number of fuzzy rules $k$ and the positions ($a$) and widths ($b$) of the input and output membership functions. Of prime importance is that FS $\in$ FRBS is an universal approximator.

*Theorem 1* (Universal approximator) Let FRBS be the set of all FS and $f : U \subseteq I\!R^n \rightarrow I\!R$ be a continuous function defined on a compact U. For each $\epsilon > 0$ there exists a $FS_\epsilon \in FRBS$ such that
$sup\{\mid f(\vec{x}) - FS_\epsilon(\vec{x}) \mid \ \mid \vec{x} \in U\} \leq \epsilon$.
Castro [15] provides the proof.

Clearly, from a theoretical point of view a FRBS performs the same actions as other universal approaches. The important thing is that the fuzzy rule-based approach is a high level, symbolic modeling technique. The fuzzy rules much more closely resemble the way humans explain general rules, so the fuzzy rule-based algorithm easily defines the function $f$.

Because a fRBS claims to better model the way humans think, the fuzzy community disputes the best and correct inference rule, the AND interpretation, and the defuzzification strategy. Most of the currently implemented applications, as well as the following, use only equations 1 - 5.

## III. NiCd batteries

There are many types of batteries used today for the storage and conversion of energy. All batteries can be defined as devices to convert energy. NiCd batteries (Fig. 2) convert the energy by chemical reactions [16]. Usually, batteries for charging with high currents have thin sintered plates as electrodes. They are wound compactly in a roll and insulated conductive from each other by a porous separator (Fig. 2). This structure is embedded in a cylindric, solid steel casing and closed with a safety vent. The compact, rolled construction of the electrodes leads to a small internal impedance and the high rate charge and discharge conditions. During charge and discharge, the following simplified reactions take place on the positive nickel and the negative cadmium electrode:

$$2\ NiOOH + 2\ H_2O + 2e^- \underset{\text{charge}}{\overset{\text{Discharge}}{\rightleftharpoons}} 2\ Ni(OH)_2 + 2\ OH^-$$

$$(U+ \ = 0.49\ V) \tag{6}$$

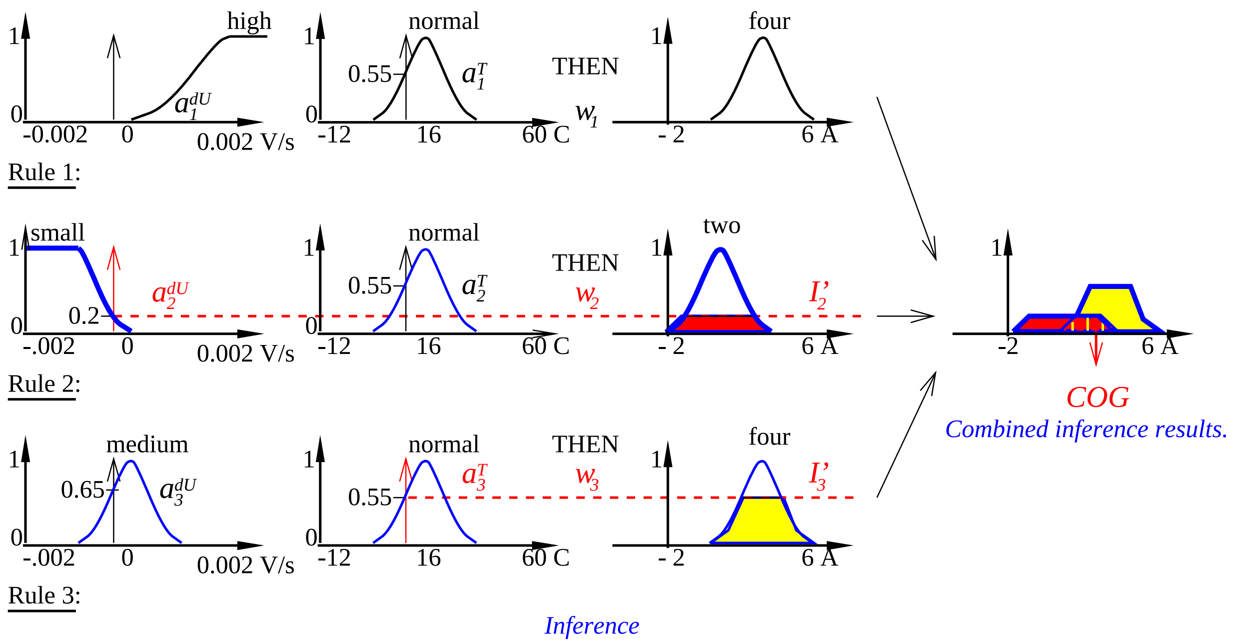


Fig. 1. Fuzzy rule-based algorithm

$$Cd + 2\ OH^- \underset{\text{charge}}{\overset{\text{discharge}}{\rightleftharpoons}} Cd(OH)_2 + 2\ e$$

$$(U - \quad = 0.809\ V). \tag{7}$$

Overall:

$$Cd + 2\ H_2O + 2\ NiOOH \underset{\text{charge}}{\overset{\text{Discharge}}{\rightleftharpoons}} 2\ Ni(OH)_2 + Cd(OH)_2$$

$$(U \quad = 1.299\ V). \tag{8}$$

Namely, at the positive electrode, changes proceed between nickel oxyhydroxide and nickel hydroxide ($NI(OH)_2$), and at the negative between cadmium metal and cadmium hydroxide ($Cd(OH)_2$). For more details see [16], [10], [17], [18]. The electrolyte potash lye $KOH$ serves only for the ion transportation and does not actively participate in the charge and discharge reaction.

These charge and discharge reactions can take place very often, which leads to the high service life of the NiCds. Besides these main reaction some unwanted other reactions, e.g., oxidation and corrosion occur especially during overcharging. There, the origin aggressive oxygen attacks the separator and builds irrevocably carbonate. The oxygen is generated because the positive electrode becomes fully charged before the negative electrode, which is larger in capacity:

$$4OH^- \longrightarrow O_2 + 2\ H_2O + 4\ e^- \tag{9}$$

These unwanted reactions make the mathematical analyses very difficult [19], [20]. Fig. 3 shows the dependance of the cell voltage and its temperature on the charge current ($6\ A$) and the ambient temperature during the charge process. The balance of the main reaction during charging is slightly negative, i.e., the cell loses heat, which compensates the Ohmic loses. However, charging with high currents leads to overcharging of the cells before the end of the process because of the limited current reception of these cells. The generated oxygen diffuses to the negative cadmium electrode and recombines. This reaction is exotherm, so that at the end of the charging process the temperature of the cell rises (Fig. 3). The voltage of a cell rises only a bit during charging. Just before reaching the full charge point, the voltage rises more and then falls, because the temperature decreases the internal resistance.

Battery packs of NiCds for motor operated drills consist of 4 - 12 cells. Each cell could be from a different vendor with different characteristics because of the delivery certainty. So, the several existing strategies for charging NiCd battery packs for motor operated tools have some disadvantages. Such strategies are:

- constant time
- $dU/dt > \epsilon$
- $dT/dt > \epsilon$
- negative $dU$
- $dT = T_{act} - T_{start} > \epsilon$

Charging for a constant time is only possible if the pack is completely empty, and will damage the pack particularly at the end of its service life. The increasing of $dU/dt$ before the local maxima of $U$ at the charging end varies with the temperature and causes difficulties in an outside environment as well as $dT/dt > \epsilon$ and $dT = T_{act} - T_{start} > \epsilon$. A negative $dU$ is an often used and good criteria, which overcharges the pack a little bit. It leads to problems at deep temperatures because of a nearly constant $U$. Taking into cosideration all these problems, today's battery charger restrict the temperature charging conditions. A just used hot battery pack can not be charged as well as a very cold pack.

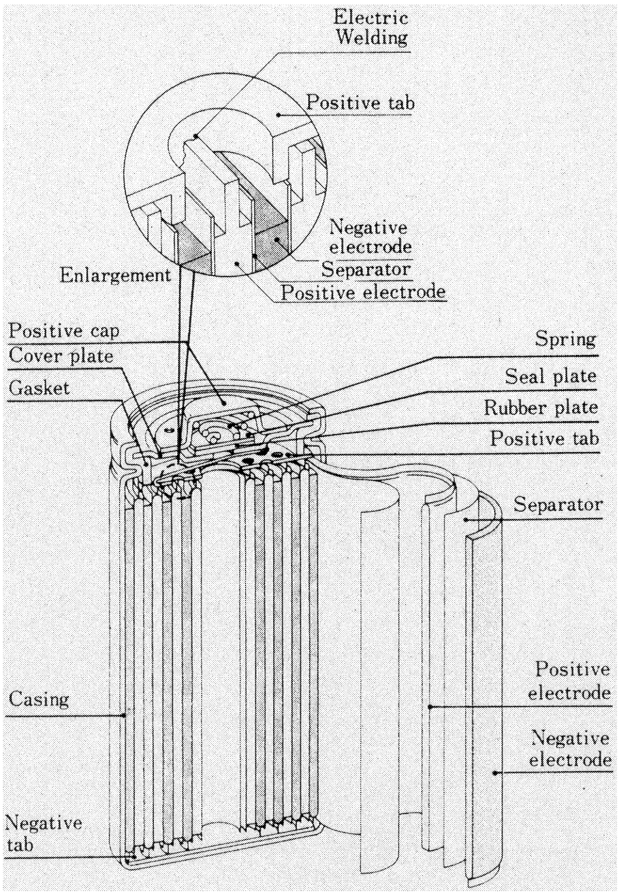


Fig. 2. Structural design of a NiCd battery

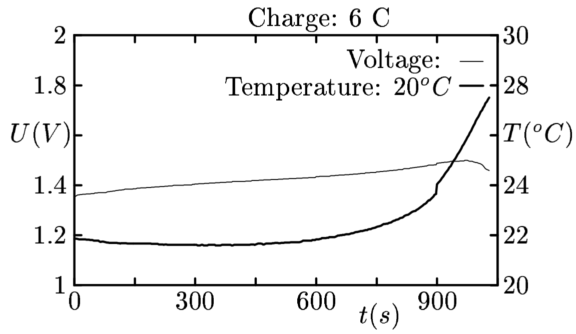


Fig. 3. Charge characteristic

With this new fuzzy system approach it is possible to consider all the mentioned hypotheses and charging methods with the compositional rule of inference in the FRBS. The input values are weighted, combined and considered simultaneously of their plausibility.

### A. Hardware

The used battery charger is 5 cm high, 12.5 cm wide, 21 cm long and consists of a primary clocked power pack (0-6A), which is controlled by a microcontroller[2] (Fig. 4). When a pack of multiple cells is discharged, differences in the residual capacity of each cell cause one of them to reach the state of complete discharge sooner than the others. As it becomes over-discharged its polarity is reversed. Therefore, each charging process begins with the initialization of the battery pack, where the pack is charged for 30 seconds with a medium current to stabilize each cell.

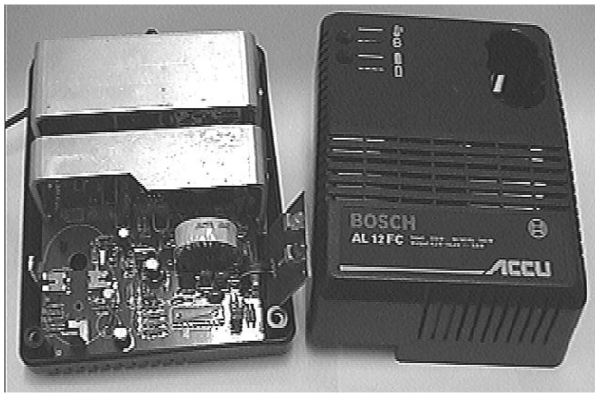


Fig. 4. Standard model of the "fuzzy" controlled battery charger

## IV. Genetic Optimization

There is no theoretical approach that defines an optimal FRB for a given task. Therefore, adaptation and optimization are methods to compute well designed FRBS. Considering all parameters of a FRB we have to deal with a very complex optimization space. Even when parts of the structure are fixed, e.g., by a hardware implementation, a lot of free parameters remain. Especially the fuzzy sets are important for fine tuning and the transfer function of the system. In contrast, the rule base is less flexible, even when the rules are weighted. A suitable optimization algorithm for the adaptation of a FRB is the genetic algorithm (GA) introduced by Holland, which is described in detail by Goldberg [5].

The basic idea is to initialize the fuzzy rules and membership function depending on $p$ input (referential) vectors $\vec{x} \in \mathbf{X}$ with a simple algorithm and to optimize them with a genetic algorithm. The referential data set contains nominal data collected by skilled users and a simplified mathematical model based on Deyuan [19], [20]. Noise is added to the mathematical model to simulate parameter variations and to improve the robustness of the system.

### A. Initialization

The initialization of the FRB takes place with fixed, Gaussian membership functions $(\mu, \sigma)$, which are regularly distributed over the universe of discourse of each linguistic variable. The membership functions overlap each other 50% and are normalized on a height of one (Fig 5). In this first step, the fixed membership functions are not a problem because they are optimized by the genetic algorithm. The subspace $U \in \mathbb{R}^n$ is divided into smaller subspaces analogous to small cubes in a bigger cube by the definition of the membership functions for each input variable and the AND conjunction (section II) of these membership functions in a fuzzy rule. Now, we generate a fuzzy rule

[2]ST6 from Thomson

for each subspace of our charging system with only four input variables. Therefore, for each component $p_i$ of a referential data set vector $p \in I\!R^n$ the membership function with the highest membership value is selected for the combination into a fuzzy rule. This new fuzzy rule is added to the rule base if no other rule of the rule base is activated with a truth value higher than a predefined $\epsilon \in ]0, 0.5]$. For systems with more than four inputs a rule is only generated if a referential vector $\vec{x}$ is in the subspace instead of the permutation of all membership functions. So, the rule base covers only the subspace of the referential data set and not the complete universe. The starting population of the GA is generated through a random shift of the fixed membership functions.

### B. Algorithm

The GA uses a population $\mathbf{P}$ of constant size $M$, i.e., a variety of $M$ fuzzy systems. The population $\mathbf{P}$ develops in discrete time steps $t$, and the populations $\mathbf{P}(t)$ are called *generations*. The algorithm terminates after $T$ time steps. The development of the population with each time step is directed by competition between population elements. The information needed is a measurement for each FRB performance quality, the *fitness* $Q$. The result of the objective function $Q$ has to be a positive value, which increases with the system performance. Competition between the population elements is included by relating this fitness to the total fitness of the population. The related measure is called *strength*. For the calculation of a new generation (genetic) operators are used, which work on a coding of the system parameter sets, named *strings*. Therefore, the population elements are completely defined by their strings $A$, so $\mathbf{P} = \{A_1, A_2, \ldots, A_M\}$.

Binary coded parameters are used to construct a string. Every string $A$ holds all fuzzy set parameters $m_{ij}$ and $\sigma_{ij}$, $i = 1, \ldots, n$, $j = 1, \ldots, q$ of a FRB (as proposed by Karr [4]). The parameters are linearly transformed into integers of $l$ bits accuracy (e.g., $l = 8$ bits) with constant limits for every variable. Denoting the coded fuzzy set parameters $\hat{m}_{ij}$ and $\hat{\sigma}_{ij}$, a string $A$ is constructed by adding the parameters in a row:

$$\begin{aligned} A &= \hat{m}_{11}\hat{\sigma}_{11}\hat{m}_{12}\hat{\sigma}_{12} \ldots\ \hat{m}_{nq}\hat{\sigma}_{nq} \\ &= \underbrace{a_1 a_2 \ldots\ a_l}_{\hat{m}_{11}} a_{l+1} \ldots\ a_L, \quad a \in \{0, 1\}. \end{aligned} \tag{10}$$

The length $L$ of a string is $L = 2lnq$.

The calculation of a new generation $\mathbf{P}(t+1)$ from $\mathbf{P}(t)$ is done by sequentially applying the operators *selection*, *mutation* and *crossing over*:

First, two strings $A, B \in \mathbf{P}$ are selected and copies $A'$ and $B'$ of $A$ and $B$ are made. The probability for the selection of a specific string is proportional to its strength.

Second, each of these two strings is changed by mutation. A mutated string $A''$ is calculated by changing every $a_i$, $i = 1, \ldots, L$ of $A'$ with the probability $p_{\mathrm{mut}}$. $B''$ is calculated the same way.

Third, with the probability $p_{\mathrm{cross}}$ a crossing over of $A''$ and $B''$ is executed. A crossing point $x$ $(1 < x \leq L)$ is chosen at random, and then new strings $A(t+1)$ and $B(t+1)$ are constructed as

$$\begin{aligned} A(t+1) &= a_1 a_2 \ldots a_{x-1} b_x b_{x+1} \ldots b_L, \\ B(t+1) &= b_1 b_2 \ldots b_{x-1} a_x a_{x+1} \ldots a_L. \end{aligned} \tag{11}$$

If no crossing over is performed, then $A(t+1) = A''$ and $B(t+1) = B''$.

The calculation of new string pairs is repeated until the new population is filled. Then the fitness of the new population members is calculated and it can be proceeded with this population.

The parameters of the algorithm can be selected as follows. Fixed values are chosen for the algorithm's random parameters, so $p_{\mathrm{mut}} = 0.01$ and $p_{\mathrm{cross}} = 0.8$ (see [5]). $M$ and $T$ will be selected according to the system complexity.

At each time step $t$ one is mainly interested in the performance of the best FRB, i.e., in the string with the highest fitness value $f$. At time step $t = T$, this string is also viewed as the result of the GA. To preserve the best string of time step $t$ from being changed by the genetic operators, this string might be copied unchanged into the next generation. This strategy called *fittest survive* does not always increase the performance of the algorithm.

For fitness calculation, a FRB has to be constructed from each string and tested by evaluating the referential data set and the simplified mathematical model. Therefore, a lot of rule base evalutations are needed. A discrete FRB with a very fast evaluation method is used for this task [21]. A further speedup is reached through the distribution of the fitness function evaluation over a local area network onto different workstations. The coding used for the GA matches the use of a discrete FRB. Furthermore, the coding limitations due to discretization and constant intervals are of small importance because FRBS are robust and the range of the DA converter is also limited.

### C. Objective function

An other problem besides the creation of coded strings is the definition of a suitable objective function. A first suitable objective function for the referential data set and the mathematical model is the reciprocal of the mean square error:

$$Q^p_{0,c} = \begin{cases} 0 & \text{, one } a_i \text{ undef.} \\ p / \sum_{i=1}^{p} (a_{ref,i} - a_i)^2 & \text{, else} \end{cases} \tag{12}$$

The analysis of the internal states of FRBS shows that the fuzzy system activates many fuzzy rules and that the overlap of the membership functions does not correspond to human expectations and definitions. Next, the objective function is modified to reduce the number of activated rules. For that the *entropy* of a FRB by the average number of activated rules is introduced [3], [22]:

$$R_\phi = \frac{\sum_{i=1}^{p} R_{act,i}}{p} \tag{13}$$

To decrease the entropy of a FRB and with it the overlap of the membership functions, a nominal number $R_{max}$ of activated fuzzy rules is defined and the objective function is modified by:

$$Q = \begin{cases} \frac{Q^p_{0,c}}{(\frac{R_{act}}{R_{max}}-1)a+(\frac{R_\phi}{R_{max}}-1)b+1} & , R_{max} < R_{act} \\ \frac{Q^p_{0,c}}{(\frac{R_\phi}{R_{max}}-1)b+1} & , \text{else} \end{cases} \quad (14)$$

$R_{max} \in \mathbf{N}$: nominal number of activated rules, $R_{act} \in \mathbf{N}$: actual number of activated rules, $a, b \in \mathbf{R}$.

The factors $a, b = 0.5$ weight the decreasing of the objective function depending on local or global limitations of the FRB.

### Notes on Genetic Algorithms

- GAs work with a population of competing solutions. Therefore, the algorithms can escape from local fitness maxima in the search (parameter) space.
- The genetic operators are probabilistic and are applied to coded parameter sets only. They are independent of the structure of the search space. Therefore, GAs are robust.
- Execution time grows linear with population size $M$, evolution steps $T$ and length of strings $L$ (under the assumption that FRB calculation time is proportional to the number of fuzzy sets).

## V. Experiments and Results

Several experiments are necessary to succeed. The first simulations with the basic objective functions of equation 12 lead to unsatisfactory results. The FC represents only the referential data set and not the general concept behind the data. On one hand the standard deviation $\sigma$ of the membership functions was too big and on the other hand too much membership functions were selected.

In the next simulation cycle the membership functions for the output variable current (Fig. 5) are fixed, random noise ($< 5\%$) is added to the simulation system of the battery pack and the number of membership functions is reduced. Now, the resulting FC was able to charge under conditions which were not represented in the referential data set with only some exceptions. Nevertheless, the membership functions still were not suitable.

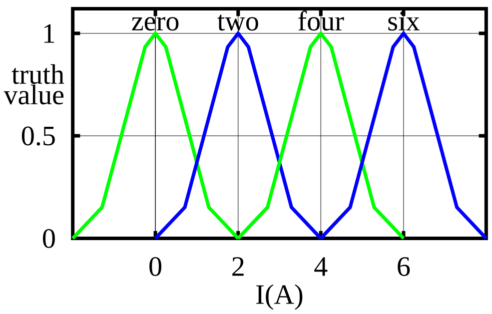


Fig. 5. Membership function of the output variable current

In the third simulation cycle, the entropy of the fuzzy system is considered in the objective function and the number of membership functions is further reduced. The resulting FRBS was able to charge the battery pack under nearly all conditions and the membership functions were also suitable. This rule base was used to test the system on the hardware platform. The rule base shows quite a good behavior on the hardware platform, except a too intensive dependency on the voltage $U$. This leads to a higher overcharging when the battery pack ages, because of the parameter variations. Simulations with ageing effects of NiCd batteries would require too much computation time.

So, for the last simulation cycle the rule generation for the membership function $\mu_{small}(u)$ of the voltage U is suppressed, which leads to the best and also a satisfying result [22], [23]. Fig. 6 shows the resulting membership functions and Table I presents some fuzzy rules. The fuzzy rules reflects the combination of charging methods described in Section III and are easily combined into the FC with the compositional rule of inference. Table II shows a comparison of the predecessor model[3] with the proposed fuzzy model on a 9.6 V battery. The predecessor model works with the negative $dU$ criteria.

TABLE I
Some fuzzy rules of the battery charger

| | |
|---|---|
| IF T is small | THEN I is two |
| IF T is high AND dT is small | THEN I is four |
| IF T is high AND dT is high | THEN I is zero |
| IF U is high | THEN I is zero |
| IF T is normal AND dT is small AND dU is high | THEN I is six |
| IF T is normal AND dT is high AND dU is high | THEN I is two |
| IF T is normal AND dU is high | THEN I is six |
| IF T is normal AND dU is small | THEN I is zero |

TABLE II
Comparison of the predecessor model with the new fuzzy controlled charger. Discharging with a constant current of $12A$ and a end voltage of $0.7\ V$ per cell.

| | **Predecessor** | **Fuzzy** |
|---|---|---|
| time (sec) | 990 | 959 |
| $T_{end} - T_{start}$ ($^oC$) | 16.5 | 9.0 |
| charge current (Ah) | 1.63 | 1.44 |
| discharge current (Ah) | 1.34 | 1.33 |
| charge efficiency (Ah/Ah) | 0.82 | 0.91 |
| charge energy (Wh) | 19.67 | 17.53 |
| discharge energy (Wh) | 11.61 | 11.84 |
| energy efficiency (Wh/Wh) | 0.59 | 0.68 |

### Notes

- Random noise increases the generalization capabilities.
- Process information can be specified in:
  - a referential data set,

[3] GAL 12, Bosch GmbH

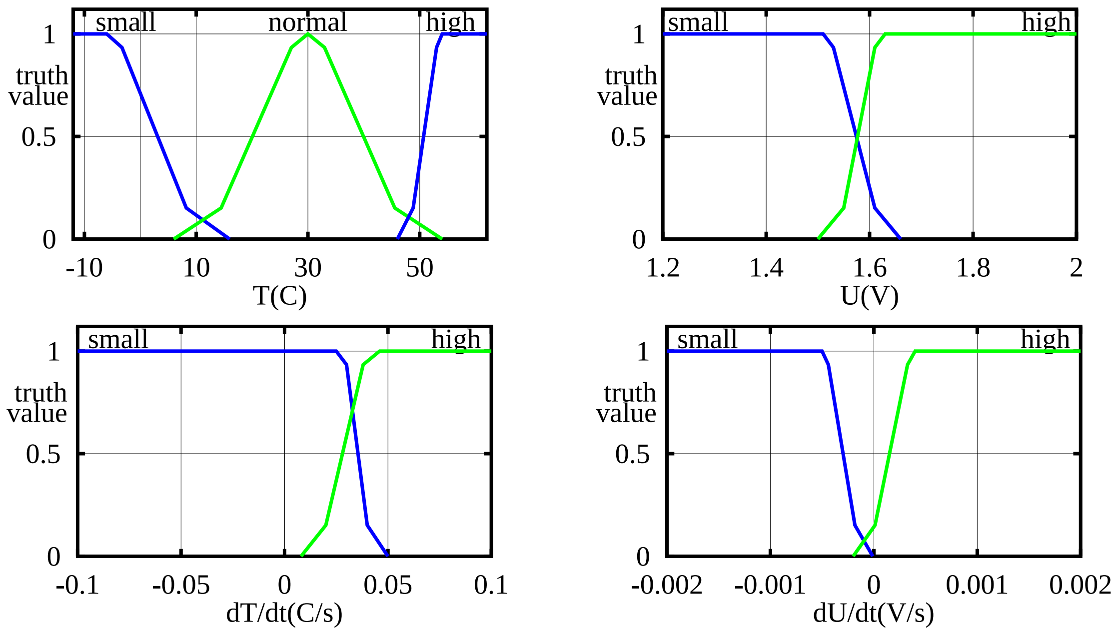


Fig. 6. Example of membership functions for the input variables

– an analytical model,
– the objective function and
– in the coding/decoding algorithm.

- Global information of the fuzzy system (entropy) is given in the objective function.
- Decoding only a part of the strings suppresses unnecessary information.

## VI. Conclusions

A genetic optimization methode of a fuzzy system for charging high power NiCd batteries was presented. The optimized fuzzy system is able to charge NiCd batteries in about 10 minutes with a current of 6A. The charging current is permanently controlled and varied depending on the state and the actual charging capabilities of the battery pack in contrast to most of the existing charging methods which uses a constant current. The resulting battery charger can be used in a wide temperature interval, and also under conditions in which standard battery chargers do not operate.

For the optimization of the fuzzy system with a standard genetic algorithm

- a special objective function was developed, which includes the consideration of the entropy of a fuzzy system,
- random noise is added to the referential data set and to a simple mathematical model and
- some information is suppressed when decoding the strings.

With the fuzzy rules it is possible to consider the plausibility of all the input values simultaneously. The several hypotheses are weighted and combined with the compositional rule of inference into the FRBS.

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**Hartmut Surmann** received his diploma in computer science from the Department of Computer Science, University of Dortmund and his Ph.D. in electrical engineering from the Faculty of Electrical Engineering, University of Dortmund, Germany, in 1989 and 1994, respectively. He is a Project Engineer in GMD System Design Technology Group in St. Augustin, Germany. His primary research interest is fuzzy control and robotics including relations to neural networks and genetic algorithms. He has published several papers in the area of design, application and hardware for fuzzy logic controllers. He is a member of the GI and VDE.

Dr. Surmann received the FUZZ-IEEE/IFES'95 robot intelligence award for a fuzzy system for indoor mobile robot navigation.