Fuzzy Prediction Control Strategy of EMS with Energy Hybridization of High Energy and High Power

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Abstract
A combination of different electric energy supply with different feature is designed for high acceleration and high ranges and improves the whole system properties. Energy supply system with energy hybridization of high energy and high power need an intelligent management system in order to control power and state of charge. In this paper we proposed a fuzzy prediction control strategy of energy management system (EMS) based on a new forward-looking and causal structure model. This control strategy is mainly consisted of three controllers, including SOC prediction controller, recharge controller and power allocation controller. Simulation result shows that the driving range, the fuel economy and efficiency of fuzzy prediction control strategy have rapidly improvement compared with simple allocation (look-up table) control strategy. In the next step we will apply this control strategy with actual EV through "dspace autobox".

Keywords
fuzzy logic, control strategy, zinc/air battery, NiMH battery, ultracapacitor, electric vehicle model

1. INTRODUCTION
An industrial national project EFRB (Mobile elektrische Enerieversorgung fuer Fahrzeuge mit grosser Reichweite und hoher Beschleunigung) was supported by the Ministry of Economy, Germany. The consortium consists of the companies DaimlerChrysler, EPCOS, VARTA, K-UTEC and the research institute BIBA and Fachhochschule Mannheim. The aim of this project is to develop an electric storage system for great mileage and high acceleration.

This new principle for the power of an electric vehicle is based on a combination of a different electric energy supply with a different feature: The Zinc/air battery supplies energy for the constant load and operates for the basic energy supply. On the other hand the NiMH-Booster battery is for the middle-term energy supply. At the same time it supports the energy requirement in long term acceleration process and as an energetic recovery system for brake process and downhill drives. For the guarantee of optimal handling characteristics, even at work peak, the Ultracap is used. This electric high performance storage-media works as a doublelayer capacitor and under extreme situations of acceleration it is able to supply the additional electric energy. Figure 1 shows a system chart.

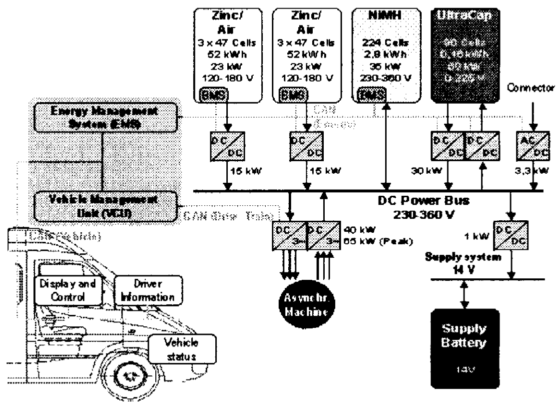


Fig. 1 System chart [Selzer et al., 2000, 2001, 2002]

The Ultracapacitor and NiMH battery enable high energy recovery during braking. They are recharged while driving by Zinc/air battery. This combination enables high driving power for short time periods as well as a wide range with medium vehicle speed. Therefore, this concept requires a complex energy management system. In the EFRB project, we propose a fuzzy prediction control strategy of EMS. Soft computing (fuzzy logic, neurocomputing and genetic algorithms are called soft computing in modern control technology) is likely to play an increasingly important role in the conception and design of systems whose MIQ (Machine IQ) is much higher than that of systems designed by conventional methods.

2. MODEL DESCRIPTION

It is necessary to build a reasonable electric vehicle model in order to analyse a different control strategy of the energy management system (EMS). Electric vehicle modeling is one method for systematic and fast investigation of the different control strategy of EMS. There are, as follows, several electric vehicle models [Hauer, 2001]: HY-ZEM (Hybrid-zero Emission Mobility) model, PNGVSAT (Program for New Generation Vehicle Systems Analysis Toolkit) model, Advisor (Advanced vehicle simulator) model, UC-Davis hydrogen model and Simplev (Simple electric vehicle simulation) model. However, a sufficient modeling program is not available today. Shortfalls of the existing model are:

(1) Insufficient modeling of transient characteristics
(2) Insufficient modeling of advanced hybrid systems
(3) Employment of a non-causal (backwards-looking) structure
(4) Significant shortcomings in the area of controls

From control strategy of EMS, none of the above models are satisfying. The investigated models compromise a number of different areas, such as separation of control algorithms from component models and causality. As a result, the models become difficult to understand. Based on this comparison a new model of EV need be proposed. Key characteristic of the new model are:

(1) Emphasis on electric vehicle
(2) Incorporation of hybrid concepts including NiMH battery and Ultracapacitor
(3) Causal structure
(4) Logical structure
(5) Incorporation of dynamics aspects
(6) Modular topology
(7) Preparation of rapid prototyping
(8) Employment of a graphical user interface (GUI)

In the EFRB project, we built the electric vehicle by using a forward-looking approach. The modeling pursues two objectives:

(1) Modularize the electric storage system in order to use multiple different battery types in one vehicle and estimate energy flows and losses.
(2) Develop an intelligent controller by fuzzy logic and optimal control to improve the efficiency of all components.

The electric vehicle model consists of the following parts: specified drive cycle, driver controller, power limitation, brake controller, vehicle, transmission, motor, energy supply system and energy management system. Figure 2 shows an electric vehicle model.

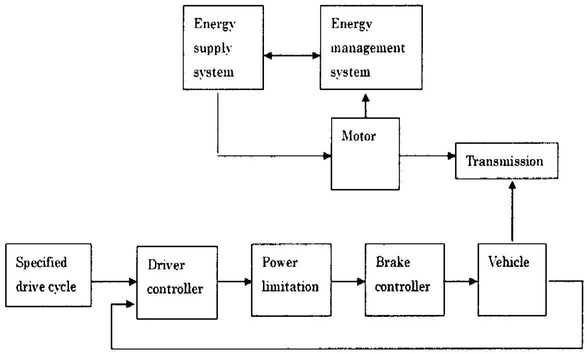


Fig. 2 Electric vehicle model [Freyberg, 2001]

3. FUZZY PREDICTION CONTROL STRATEGY OF EMS

3.1 Fuzzy logic and fuzzy logic toolbox

Fuzzy logic is a convenient way to map an input space to an output space. The primary mechanism for doing this is a list of if-then statements called rules. All rules are evaluated in parallel and the order of the rules is unimportant. Fuzzy sets and a membership function (MF) are the most important concepts in fuzzy logic. Fuzzy sets describe vague concepts. It admits the possibility of partial membership in it. MF is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership between 0 and 1).

The Fuzzy Logic Toolbox is a collection of function built on the MATLAB numeric computing environment. It provides tools to create and edit fuzzy inference systems (FIS) within the frame of MATLAB, or you can integrate your fuzzy systems into simulations with simulink. In the Fuzzy Logic Toolbox, there are five parts of the fuzzy inference process: fuzzification of the input variable, application of the fuzzy operator (AND or OR) in the antecedent, implication from the antecedent to the consequent, and aggregation of the consequents across the rules and defuzzification. Figure 3 shows a fuzzy inference diagram. The fuzzy inference diagram is the composite of all the smaller diagrams. It simultaneously displays all parts of the fuzzy inference process. Information flow through the fuzzy inference dia-

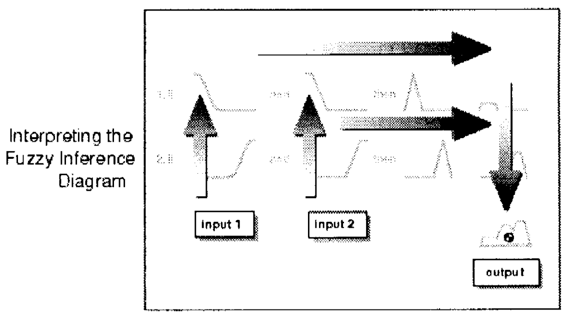


Fig. 3 Fuzzy inference diagram

gram are shown in this figure.
There are five primary GUI (Graphical User Interface) tools for building, editing and observing FIS in the Fuzzy Logic Toolbox: the fuzzy inference system editor, the membership function editor, the rule editor, the rule viewer and the surface viewer.

3.2 Fuzzy prediction control strategy of EMS

Figure 4 shows a diagram of fuzzy prediction control strategy of EMS. The main parts of this control strategy are consisted of three controllers, including SOC prediction controller, recharge controller and power allocation controller. The request power and its increment are input to block of SOC prediction controller. This controller produces desire SOC of three energy components. The recharge controller compares the difference between desire SOC and actual SOC. The output of the recharge controller includes power increment of three energy components. Power division will be performed by power allocation controller. Fuzzy inference will be applied in the three controllers.

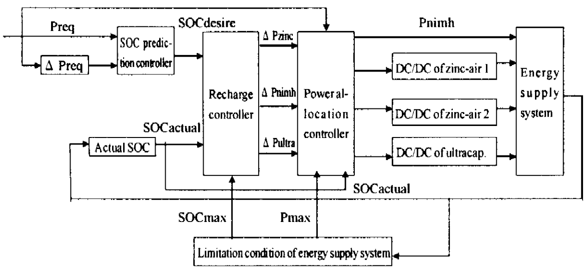


Fig. 4 Diagram of fuzzy prediction control strategy

3.2.1 Fuzzy SOC prediction controller

The inputs of SOC prediction controller include the request power and its increment. The outputs of SOC prediction controller include SOC of the three energy components. Each of the inputs and outputs has a different number of fuzzy sets.

Table 1 Fuzzy relationship between input 1, input 2 and output 1 (input 1--the request power, input 2--the power increment, output 1--SOC of Zinc/air battery)

Output1 \ Input1 / Input2	NB	NM	NS	ZE	PS	PM	PB
NE	/	/	/	/	PM	PB	PB
ZE	/	/	/	/	PM	PB	PB
PO	/	/	/	/	PB	PB	PB

Where :
NB---negative big NM---negative middle
NS--- negative small ZE---zero
PS---positive small PM--- positive middle
PB---positive big NE---negative
PO---positive

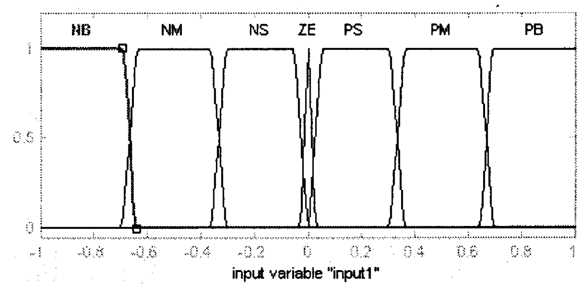
Table 2 Fuzzy relationship between input 1, input 2 and output 2 (input 1--the request power, input 2--the power increment, output 2--SOC of NiMH battery)

Output2 \ Input1 / Input2	NB	NM	NS	ZE	PS	PM	PB
NE	PS	PM	/	PM	/	PS	PB
ZE	PS	PM	/	PM	/	PM	PB
PO	PS	PM	/	PB	/	PB	PB

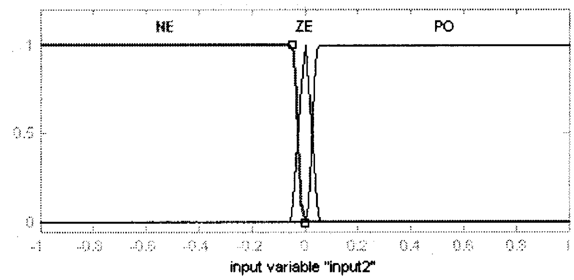
Table 3 Fuzzy relationship between input1, input 2 and output 3 (input 1--the request power, input 2--the power increment, output 3--SOC of Ultracapacitor)

Output3 \ Input1 / Input2	NB	NM	NS	ZE	PS	PM	PB
NE	PS	PS	PS	/	/	/	PS
ZE	PM	PM	PM	/	/	/	PM
PO	PB	PB	PB	/	/	/	PB

Figure 5 shows membership functions of two inputs.



(a) Input 1--the request power



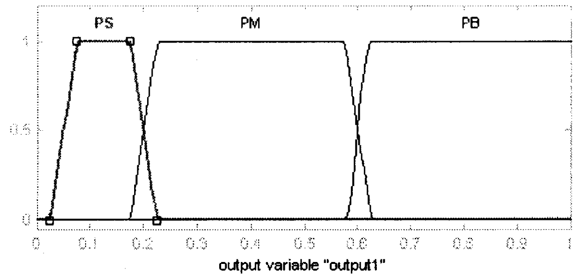
(b) Input 2--the increment of request power

Fig. 5 Membership functions of two inputs

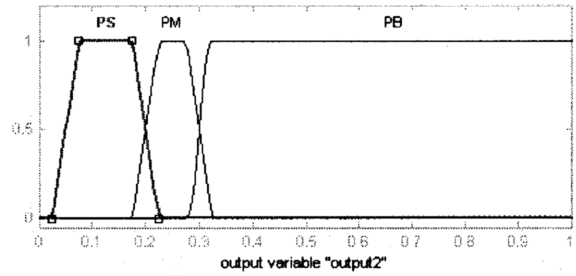
Figure 6 shows membership functions of three outputs.

3.2.2 Fuzzy recharge controller

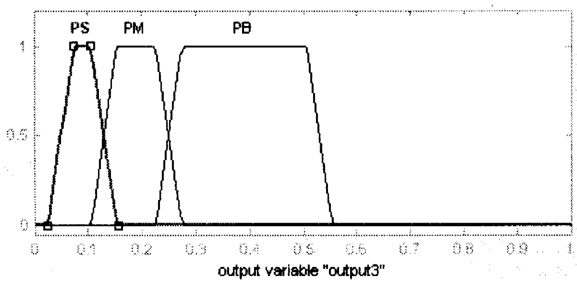
The inputs of the recharge controller consist of the SOC increment of NiMH battery (ΔSOC_{nimh}) and the SOC increment of Ultracapacitor (ΔSOC_{ultra}). The outputs of the recharge controller consist of recharge factor of NiMH battery for Ultracap ($S_{nimh-ultra}$), recharge factor of Ultracapacitor for NiMH battery ($S_{ultra-nimh}$), recharge factor of Zinc/air battery for NiMH battery ($S_{zinc-nimh}$) and recharge factor of Zinc/air battery for Ultracap ($S_{zinc-ultra}$).
Figure 7 shows membership functions of two inputs.
Figure 8 shows membership functions of four outputs.



(a) Output 1-- SOC_{zinc}



(b) Output 2-- SOC_{nimh}



(c) Output 3-- SOC_{ultra}

Fig. 6 Membership functions of three outputs

Table 4 Fuzzy relationship between input 1, input 2 and output 1 (input 1--SOC increment of NiMH battery, input 2--SOC increment of Ultracapacitor, output 1--recharge factor of NiMH battery for Ultracap)

Output1 / Input1 / Input2	NB	NM	NS	ZE	PS	PM	PB
NB	/	/	/	/	/	PM	PB
NM	/	/	/	/	/	PM	PM
NS	/	/	/	/	PS	PS	PS

Table 5 Fuzzy relationship between input 1, input 2 and output 1 (input 1--SOC increment of NiMH battery, input 2--SOC increment of Ultracapacitor, output 2--recharge factor of Ultracap for NiMH battery)

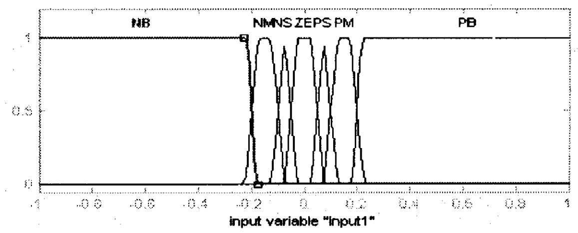
Output2 / Input1 / Input2	NB	NM	NS	ZE	PS	PM	PB
PS	/	/	PS	/	/	/	/
PM	PM	PM	PS	/	/	/	/
PB	PB	PM	PS	/	/	/	/

Table 6 Fuzzy relationship between input 1, input 2 and output 1 (input 1--SOC increment of NiMH battery, input 2--SOC increment of Ultracapacitor, output 3--recharge factor of Zinc/air battery for Ultracap)

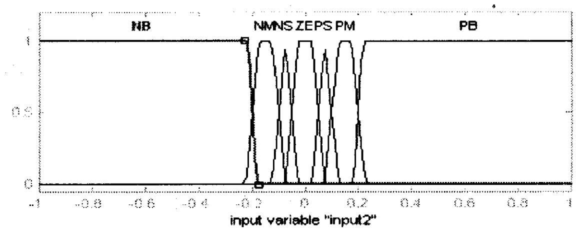
Output3 / Input1 / Input2	NB	NM	NS	ZE	PS	PM	PB
NB	PB	PB	PB	PB	PB	PM	/
NM	PM	PM	PM	PM	PM	/	/
NS	PS	PS	PS	PS	/	/	/

Table 7 Fuzzy relationship between input 1, input 2 and output 1 (input 1--SOC increment of NiMH battery, input 2--SOC increment of Ultracapacitor, output 4--recharge factor of Zinc/air battery for NiMH battery)

Output4 / Input1 / Input2	NB	NM	NS	ZE	PS	PM	PB
PS	PB	PM	/	/	/	/	/
ZE	PB	PM	PS	/	/	/	/
NS	PB	PM	PS	/	/	/	/
NM	PB	PM	PS	/	/	/	/
NB	PB	PM	PS	/	/	/	/



(a) Input 1--SOC increment of NiMH battery



(b) Input 2--SOC increment of ultracapacitor

Fig. 7 Membership functions of two inputs

3.2.3 Fuzzy power allocation controller

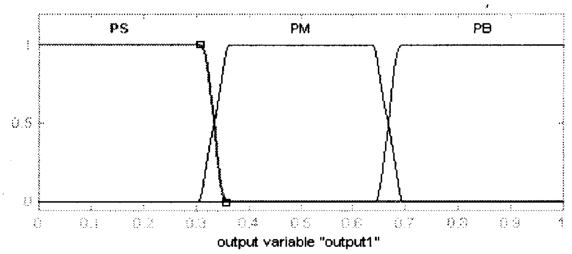
The inputs of the power allocation controller include the request power, SOC of actual NiMH battery and SOC of actual Ultracapacitor. The outputs of the controller include the power division factors of three energy components.

(1) When SOC of Ultracap. is greater (See Table 8, 9, and 10)

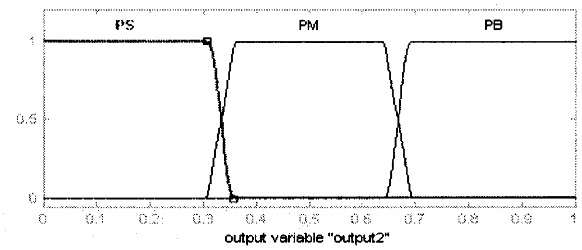
(2) When SOC of Ultracap. is not greater (See Table 11, 12, and 13)

Figure 9 shows membership functions of three inputs.

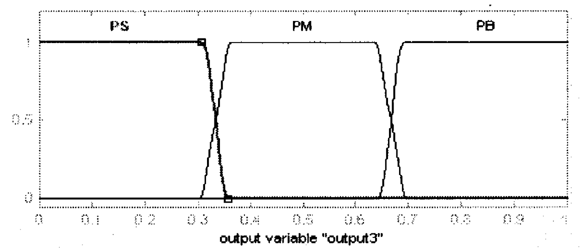
Figure 10 shows membership functions of three outputs.



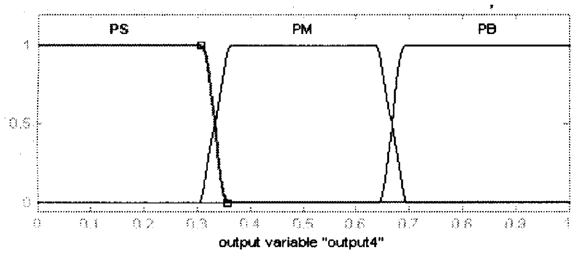
(a) Output 1--recharge factor of NiMH battery for Ultracap.



(b) Output 2--recharge factor of Ultracap. for NiMH battery



(c) Output 3--recharge factor of Zinc/air battery for Ultracap.



(d) Output 4---recharge factor of Zinc/air battery for NiMH battery

Fig. 8 Membership functions of four outputs

Table 8 Fuzzy relationship between input 1, input 2 and output 1 (input 1--the request power, input 2--SOC of NiMH battery, output 1--power division factor of Zinc/air battery)

Input1 / Output1 / Input2	NB	NM	NS	ZE	PS	PM	PB
GR	ZE	ZE	ZE	ZE	PB	PB	PB
Not GR	ZE	ZE	ZE	ZE	PB	PB	PB

Table 9 Fuzzy relationship between input 1, input 2 and output 1 (input 1--the request power, input 2--SOC of NiMH battery, output 2--power division factor of NiMH battery

Input1 / Output2 / Input2	NB	NM	NS	ZE	PS	PM	PB
GR	NB	NM	NM	ZE	ZE	PM	PM
Not GR	NB	NB	NM	ZE	ZE	ZE	PS

Table 10 Fuzzy relationship between input 1, input 2 and output 1 (input 1--the request power, input 2--SOC of NiMH battery, output 3--power division factor of Ultracap.)

Input1 / Output3 / Input2	NB	NM	NS	ZE	PS	PM	PB
GR	NB	NM	ZE	ZE	ZE	ZE	PS
Not GR	NB	NS	ZE	ZE	ZE	PM	PM

Table 11 Fuzzy relationship between input 1, input 2 and output 1 (input 1--the request power, input 2--SOC of NiMH battery, output 1--power division factor of Zinc/air battery)

Input1 / Output1 / Input2	NB	NM	NS	ZE	PS	PM	PB
GR	ZE	ZE	ZE	ZE	PB	PB	PB
Not GR	ZE	ZE	ZE	ZE	PB	PB	PB

Table 12 Fuzzy relationship between input 1, input 2 and output 1 (input 1--the request power, input 2--SOC of NiMH battery, output 2--power division factor of NiMH battery

Input1 / Output2 / Input2	NB	NM	NS	ZE	PS	PM	PB
GR	NB	NS	ZE	ZE	ZE	PM	PM
Not GR	NB	NM	NS	ZE	ZE	PS	PM

Table 13 Fuzzy relationship between input 1, input 2 and output 1 (input 1--the request power, input 2--SOC of NiMH battery, output 3--power division factor of Ultracap.)

Input1 / Output3 / Input2	NB	NM	NS	ZE	PS	PM	PB
GR	NB	NB	NM	ZE	ZE	ZE	PS
Not GR	NB	NM	NS	ZE	ZE	PS	PS

4. SIMULATION RESULTS AND CONCLUSION

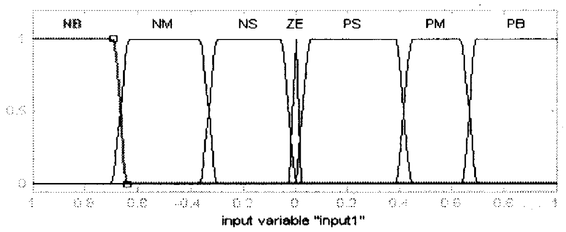
The EV performance is appraised by five key parameters [Wong et al., 2001], namely the maximum speed, the acceleration rate, the gradeability, the driving range per refuel and the fuel economy. The maximum speed is namely the quoted maximum safe speed in km/h. The acceleration rate is represented by the minimum time that an EV can accelerate from still to a particular speed on a level road. The gradeability is the hill-climbing capability, which is defined as the maximum percentage gradient that an EV can climb up at a particular speed. The driving range per refuel stands for the EV driving range in km when the corresponding energy sources have been fully charged and/or refueled. The fuel economy is measured as the driving distance per electricity consumption in km/kwh.

(1) The maximum speed:

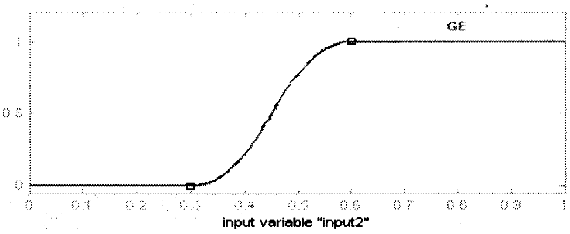
The maximum speed of this model is 95km/h.

(2) The acceleration rate: See Table 14

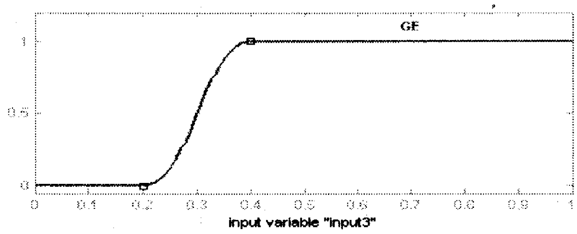
(3) The gradeability: See Table 15



(a) Input 1--the request power



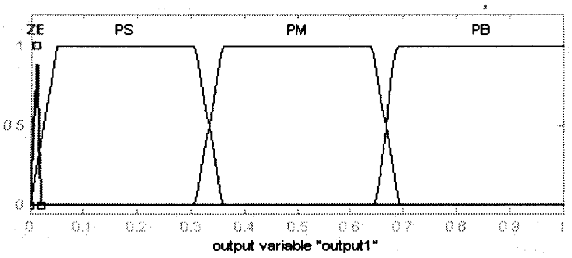
(b) Input 2-- SOC_{nimh}



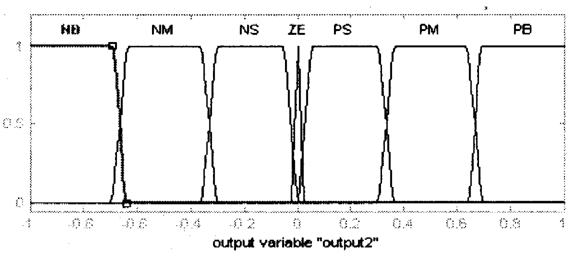
(c) Input 3-- SOC_{ultra}

Where: LE--less GE--great

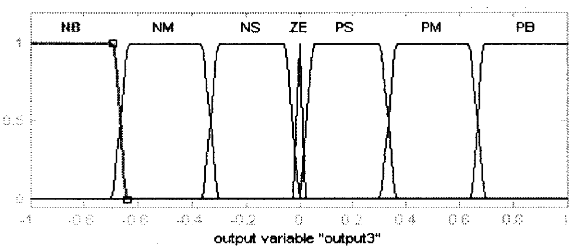
Fig. 9 Membership functions of three inputs



(a) Output 1-- S_{zinc}



(b) Output 2-- S_{nimh}



(c) Output 3-- S_{ultra}

Fig. 10 Membership functions of three outputs

Table 14 The acceleration rate of this model

Gear	Particular speed (km/h)	Minimum time (s)
1	15	1.3
2	35	4.7
3	60	14.8
4	80	31.2
5	95	67.7

Table 15 The gradeability of this model

Gear	Particular speed (km/h)	Max. percentage gradient
1	15	28% (α=16°)
2	35	10% (α=5.7°)
3	60	4% (α=2.3°)

From Figure 11 and Figure 12, we can see that the driving range, the fuel econmoy and the efficiency increase with the increase of simulation step size. The reason is that lost energy reduces with the increase of simulation step size.

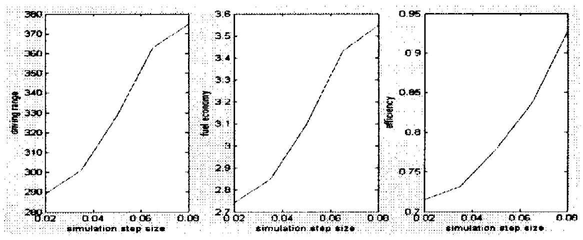


Fig. 11 Relationship of the driving range, the fuel economy and efficiency with the simulation step size for ECE cycle

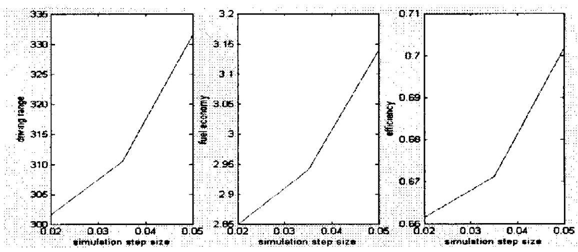


Fig. 12 Relationship of the driving range, the fuel economy and efficiency with the simulation step size for UDDC cycle

Simulation results of fuzzy prediction control strategy are shown as follows in Table 16 compared with simple allocation (look-up table) control strategy for ECE cycle. From Table 16, we can clearly see that the driving range, the fuel economy and efficiency of fuzzy prediction con-

Table 16 Simulation results of fuzzy prediction control strategy compared with simple allocation control strategy

	Simple allocation control strategy [Freyberg, 2001]	Fuzzy prediction control strategy
The driving range (km)	268.55	328.72
The fuel economy (km/kwh)	2.55	3.11
The efficiency	0.6776	0.7795

($SOC_{nimh-init}$=0.55, $SOC_{ultra-init}$=0.35, Simulation step size=0.05) trol strategy have rapidly improvement compared with simple allocation control strategy.

5. OUTLOOK

All components of the electric drive train are connected via CAN Bus. The energy management uses the CAN bus to get data and to set the parameters to the components. The control unit for the prototyping of energy management is a "dspace autobox". The energy management is realized in Matlab/Simulink. In the next step, we will apply the proposed control strategy with actual EV according to present situation.

The modeling of EMS of energy hybridization of EV poses a considerable challenge. In the EFRB project, we further demonstrate the application of an artificial neural network (ANN) to model the EMS. The model maps SOC of three energy storage components and the requirement power to the allocated power of Zinc/air battery and Ultracapacitor (see Figure 13).

The proposed energy management concept can not only be used for this type of vehicle, it can also be applied to other types of drive trains with combustions engines and electric generators, with fuel cells or with other energy sources like photovoltaic systems.

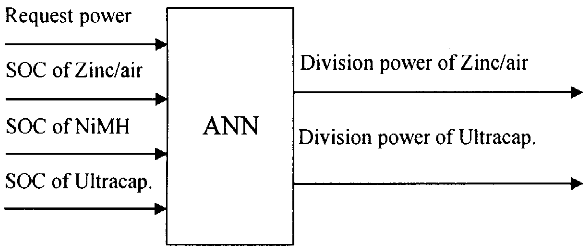


Fig. 13 Diagram of artificial neural network (ANN)

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