Available online at www.sciencedirect.com
ScienceDirect
Journal of Power Sources 158 (2006) 936–943
JOURNAL OF POWER SOURCES
www.elsevier.com/locate/jpowsour

ANN modeling of cold cranking test for sealed lead-acid batteries

Hassan Karami[a,*], Mohammad Ali Karimi[b], Maryam Mahdipour[c]

[a] Aranniru Battery Manufacturing Co., AMICO Industrial Group, Tehran, Iran
[b] Department of Chemistry, Faculty of science, Payame-Noor University of Ardakan, Ardakan, Iran
[c] R&D Center, Sepahan Battery Industrial Complex, Oshtorjan Industrial Zone, Isfahan, Iran

Available online 15 December 2005

Abstract

A cold cranking test for 17 sealed lead-acid batteries with grids of lead–calcium alloy at −18 °C was performed at different discharge currents. Time–voltage behavior of the batteries during 10 s discharge, voltage values at discharge times of 30, 60 and 90 s, and time of discharge to reach a final voltage of 6 V are critical points in the cold cranking test. These were modeled by artificial neural networks in MATLAB 7 media. Nine discharge currents were used for the training set, five discharge currents for the prediction set and three discharge currents for the validation set. Maximum prediction errors in the modeling of the time-voltage behavior during a 10 s discharge (model 1), the voltage of critical points of 30, 60, 90 s (model 2) and the time to reach a final voltage of 6 V (model 3) were under 3.1%, 3.3%, and 3.5%, respectively for each model. The results obtained showed that the models can be used in the battery industry for the prediction of the cold cranking behavior of lead-acid batteries at high discharge currents based on experimental cold cranking data at low discharge currents without the use of expensive and complex instruments. A file (EXE file) based on the model obtained by WinNN 32 was prepared to enable inexpert operators in the lead-acid battery industry to use the method.

Keywords: Cold cranking; CCA; Artificial neural network; Model; Sealed lead-acid batteries

1. Introduction

With ever increasing concerns over environmental protection, energy conservation and energy efficiency in recent years, research and development on technology of various batteries is being actively conducted. Due to its mature technology, lower cost and modest performance, lead-acid batteries, are still widely used in the most commercially available vehicles and other applications. Moreover, the present great foreseeable future, it is almost impossible for other advanced batteries to replace lead-acid batteries completely in vehicles.

Cold cranking amps (CCA) is a rating used in the battery industry to define a battery's ability to start an engine in cold temperatures. CCA can be defined in different conditions. In other words, any manufacturer or any standard can define the CCA with different critical control values. For example, CCA can be defined as a rating that in this rating, the current amount in amp which, a new fully charged battery can deliver at 0 °F (−18 °C) for 30 s, while maintaining a voltage of at least 7.5 V, for a 12 V battery. The higher CCA rating shows the greater the starting power of the battery. Because of the above mentioned importance of cold cranking ability, it is seemed that modeling and prediction of CCA for lead-acid batteries is very interest and important.

Mathematical models of physical and chemical systems were constructed to facilitate our understanding of mechanisms and to lead to specific responses and to enable prediction of responses. They are constructed in two basic frameworks: deductive (or phenomenological) and inductive (or data based). Models are built in the phenomenological framework in most areas of science and engineering as a reflection of our desire to understand the fundamental mechanisms underlying complex phenomena. Inductive models are parametric frameworks with data based selection or training of the parameters. They usually seek to simulate excitation/response or input/output relations as interpolations among measured data, and they do so through adjustment of their parameters in a training process. Artificial neural networks (ANN) are frameworks that accomplish this type of mapping.

At recent years, many attempts were concerned to use of mathematical methods for modeling of some characteristics of lead-acid batteries. Modeling of lead-acid batteries

* Corresponding author. Fax: +98 21 6427263.
E-mail address: karami_h@yahoo.com (H. Karami).

0378-7753/$ – see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.jpowsour.2005.11.024

based on impedance measurements has become very important recently with several groups reporting results in this area [1–5].

Traditionally, the estimation of the battery available capacity (BAC) under variable discharge currents has been presented by the estimation of the battery state-of-charge (SOC). There are many reports describing various attempts to estimate the SOC using various computational approaches, the initial report about the determination state-of-charge and state of health of batteries by fuzzy logic methodology [6] was presented in 1999 in Brighton, England. The other reports at this field were presented in literature or meetings [7–11]. The major of earlier reports were mainly concerned with small VRLA cells of 1–2.5 Ah capacity. After that other experts reported an impedance modeling of intermediate size lead-acid batteries used in army tanks [12–14].

Some direct estimation methods of the BAC have ever been explored. Recently, the estimation accuracy of the BAC has been significantly improved using the artificial neural network model [15]. For the variable discharge current, the published methods for the calculation of the BAC can be categorized into two groups-either based on the average discharge current or based on the reference discharge current [16–19].

At the recent decade, the artificial neural networks (ANNs) have been widely interested as a mathematical strong model for some characteristics of lead-acid batteries [20–23].

Based on our best knowledge, there is only one report about modeling of cold cranking test [24]. In the present work, the use of ANNs for the inductive modeling of input/output relations in lead-acid batteries for knowing about the behavior of cold cranking Amps (CCA) has been explained. The CCA computation model based on the artificial neural network (ANN) for lead-acid batteries is presented. The results of experiments have proven the further improvement of accuracy and precision with the proposed model. The final models were used in WinNN 32 for making a EXE file for inexpert operators in industries of lead-acid batteries in order to prediction of cold cranking behavior at high discharge currents and in order to determine of acceptable amount of CCA based on experimental low discharge currents data for a lead-acid battery as a non-destructive test.

2. Experimental

2.1. Reagents and materials

All material and reagents used in experiments were in industrial grade and all of them were obtained from Iranian companies. All sealed lead-acid batteries with capacity of 50 Ah used in the study were produced by Sepahan Battery Co. (Isfahan, Iran).

2.2. Instrumental

Making of low temperature (−18 °C) was carried out by industrial freezer (ARMMD FB, Iran). Cold cranking tests were performed by discharge instrument (HEW1500-12, Digatron, Germany).

2.3. Methods

All sealed lead-acid batteries used in the study were the same in open circuit voltage (OCV), weight, power and battery available capacity (BAC). Before performing of each cold cranking test, each battery was hold at −18 °C for 24 h. Each battery was used only for one discharge current in cold cranking test. At a cold cranking test, first the battery was discharged under a known constant discharge current (I) for 10 s. The interval time for reading of discharge voltage was 1 s. Second, the battery was discharge under current of 0.6I (I = CCA) to reach final voltage of 6 V. In second section, critical times for record of voltage were 30, 60, 90 s and the time of reaching to 6 V. Three models were separately used for first 10 s discharge data, critical voltage of 30 s (V_{30}), 60 s (V_{60}) and 90 s (V_{90}) and for time of reaching to final voltage of 6 V ($t_{6\,V}$). Each modeling was performed by nine discharge currents in training set, five discharge currents in prediction set. The obtained models were validated by three different discharge currents. All steps of modeling were carried out in MATLAB 7 media.

The lead-acid battery with nominal voltage 12 V is used for exemplification, whose available capacity is 50 Ah at the 20 h discharge rate and temperature of 40 °C. For modeling of CCA at constant temperature of −18 °C, different discharge currents are selected to discharge the batteries, namely 50, 100, 150, 200, . . . and 850 A. The cutoff voltage of 6 V is used for all discharges. Based on the aforementioned conditions, the following test plans are performed and last over 10 days, until a complete set of data is collected.

The procedure had following steps:

1. Selection of 17 sealed lead-acid batteries, which are the same in open circuit voltage (OCV), weight, power and battery available capacity (BAC = 50 Ah).
2. Charging of the batteries using the same charge algorithm until the battery is fully charged.
3. Place the battery in the freezer for 24 h to have constant temperature of 0 °F (−18 °C).
4. Discharge of the battery at different currents for 10 s namely 50, 100, 150, . . ., and 850 A (each battery use only for one discharge current and the interval time for reading of discharge voltage was 1 s).
5. After a rest for 10 s, discharge of the battery by $0.6 \times I_{cc}$, namely 0.6×50 A, 0.6×100 A, 0.6×150 A, . . ., and 0.6×850 A (critical times for record of voltage are 30, 60, 90 s and the time of reaching to 6 V).
6. The important and interesting data on discharge time to reaching final voltage of 6 V classified into three groups, and each group of the data was separately modeled as following:
   (a) Model 1 was used for first 10 s discharge data for different discharge currents (I).
   (b) Model 2 was used for critical voltages of 30 s (V_{30}), 60 s (V_{60}) and 90 s (V_{60}) under different discharge currents ($0.6 \times I$).
   (c) Model 3 was used for time of reaching to final voltage of 6 V ($t_{6\,V}$) at different discharge currents.

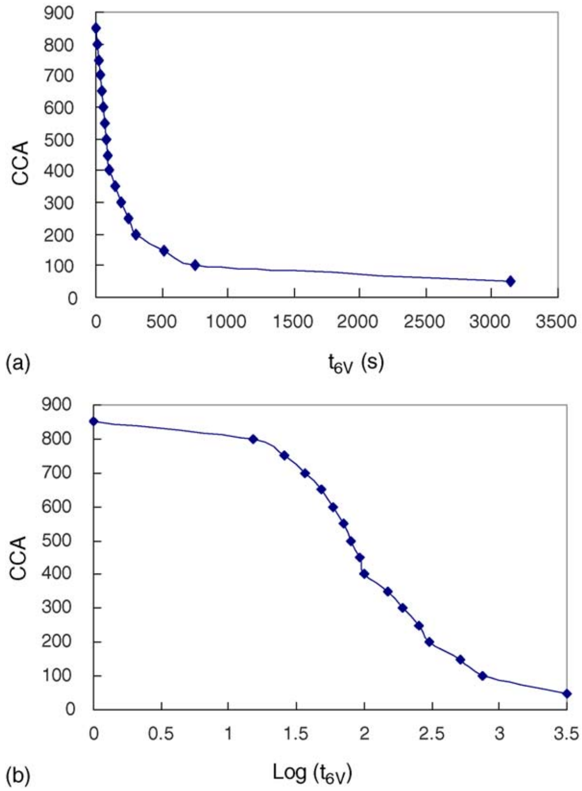

Fig. 1. Variation of (a) $t_{6\,\mathrm{V}}$ and (b) $\log(t_{6\,\mathrm{V}})$ with amount of discharge current at cold cranking test (CCA).

7. The models obtained were used for making of an EXE file for use in industrial laboratories for prediction of CCA amount of a battery based on cold discharge data at many low discharge currents (three or four low discharge currents for example 50, 100, 150 and 200 A).

It should be noted that in model 3, $\log(t_{6\,\mathrm{V}})$ was used for modeling. Fig. 1 shows relation type of CCA-$\log(t_{6\,\mathrm{V}})$ and CCA-$t_{6\,\mathrm{V}}$. To train the ANN model using the sigmoid transfer function and a learning process will be carried out, which is achieved by adapting the connection weights in response to a number of training points of discharge current (I). The aim is to arrive at a unique set of weights that are capable of correctly associating all the discharge currents with their desired voltages or time ($t_{6\,\mathrm{V}}$). The initial training of network was carried out by all data including training and prediction sets for optimizing of learning rate and momentum. The training of network was controlled by prediction error. After initial training, the model was trained without prediction set with the same learning rate and momentum for optimizing of weights and iterations. After this training, the obtained model was used for prediction of data in prediction set which this test is called as internal validation. At final step, the model was employed for prediction of data in validation set which this test is called as external validation. The final model was used in Win NN 32 software for making of an EXE file for use by inexpert operator in industries of lead-acid batteries. The EXE file has been used in quality control laboratory of Aranniru Battery Co. from 2003-10-29 for prediction of CCA amount for lead-acid batteries and for accuracy test of CCA labeled in lead-acid batteries, which are sent to the quality control laboratory.

3. Results and discussion

Cold temperatures dramatically reduce the effectiveness of chemical reactions within the battery, while increasing the battery's internal resistance, thus the cranking power will reduce as temperatures drop. The vehicle performance in cold temperature is strong relevant to the CCA, and the discharge current has a significant effect on the CCA. In the other word, the battery cranking capacity (BCC) is the electrical charge that the battery can deliver under the specified discharge current and the reference time and temperature. It is determined by the available surface of active material contained in the battery and how much of this material undergoes reaction before the battery can no longer deliver the specified current at the cutoff voltage. From its definition, the CCA is highly dependent on both the discharge current and the temperature. A rapid increase in the discharge current can severely reduce the BCC. There are two major reasons. First, during a rapid discharge, the electrochemical reactions take place mostly on the surface of the plates due to the limited time for the diffusion of the electrolyte into the pores of the active material. Second the reaction product resulting from a rapid discharge tends to close off the pores and further restrict the ingress of the electrolyte. The CCA and BCC decrease with temperature reduction. This is mainly due to the increment in the viscosity of the electrolyte and a concomitant decrease in the diffusion rate of ions to the reaction sites. Hence, it caused to add the concentration polarization of the battery. In addition of this increase in the concentration polarization, there is also an increase in the electrode polarization, so that the battery cut off voltage is reached earlier. Hence, less charge can be delivered at a given discharge current.

Because of this fact that in major of international quality control standards and quality control centers of lead-acid industries, all cranking tests are carried out at a constant temperature of $-18\,^{\circ}\mathrm{C}$ for vehicle batteries, in this work, CCA is discussed in the constant temperature as a cold cranking at $-18\,^{\circ}\mathrm{C}$. Really, the proposed models only provide amounts of voltage at different times of discharge and the time of reaching to final voltage of 6 V with respect to discharge current (CCA). The suitable CCA for a battery should be selected with respect to the request standard conditions about CCA. CCA is really a discharge current at $-18\,^{\circ}\mathrm{C}$ with respect to some critical conditions. For example, in Iranian national standard [25], IEC [26] and Peugeot standard [27] following critical conditions is used for CCA selection:

1. Discharge voltage of 10 s should not be lower than 7.5 V.
2. Time of reaching to discharge voltage of 6 V should not be lower than 90 s for small and medium batteries and not be lower than 150 s for large batteries.

In initial modeling, we collect the data as following:

All batteries were discharged at different currents (I) namely 50, 100, 150, . . ., and 850 A for 10 s. Each battery was

Table 1
Experimental data for training, prediction and validation sets for model 1

Voltage (V)	Current (A)																
	Training set									Prediction set					Validation set		
	50	150	250	350	450	550	600	700	850	100	300	400	650	800	200	500	750
V_1	11.77	10.55	9.51	8.69	7.71	7.19	6.73	5.68	4.88	11.12	9.08	8.16	6.12	5.08	9.95	7.46	5.18
V_2	11.61	10.40	9.38	8.62	7.66	7.14	6.69	5.63	4.82	10.99	8.98	8.10	6.08	5.04	9.83	7.42	5.11
V_3	11.54	10.32	9.33	8.60	7.64	7.12	6.66	5.59	4.77	10.91	8.95	8.08	6.06	4.99	9.77	7.40	5.06
V_4	11.49	10.28	9.31	8.59	7.62	7.09	6.64	5.56	4.71	10.86	8.93	8.07	6.03	4.94	9.74	7.38	5.02
V_5	11.45	10.26	9.30	8.58	7.61	7.07	6.62	5.52	4.64	10.82	8.93	8.06	6.00	4.89	9.73	7.36	4.97
V_6	11.41	10.24	9.29	8.58	7.59	7.05	6.59	5.48	4.57	10.80	8.92	8.05	5.97	4.82	9.72	7.34	4.91
V_7	11.38	10.23	9.29	8.57	7.58	7.02	6.57	5.44	4.48	10.78	8.92	8.03	5.94	4.71	9.71	7.33	4.85
V_8	11.35	10.22	9.28	8.56	7.56	7.00	6.55	5.39	4.37	10.77	8.91	8.02	5.91	4.49	9.70	7.31	4.76
V_9	11.33	10.22	9.28	8.56	7.54	6.98	6.52	5.33	3.60	10.77	8.91	8.01	5.87	3.94	9.70	7.29	4.42
V_{10}	11.32	10.22	9.28	8.55	7.53	6.95	6.50	5.26	2.80	10.76	8.90	8.00	5.83	3.44	9.69	7.27	4.08

Table 2
Experimental data for training, prediction and validation sets for model 2

Voltage (V)	Current (A)																
	Training set									Prediction set					Validation set		
	50	150	250	350	450	550	600	750	850	100	300	400	650	800	200	500	700
V_{30}	11.50	10.90	10.16	9.65	8.94	8.47	8.23	5.20	3.80	11.16	9.91	9.25	7.64	4.50	10.43	8.74	7.14
V_{60}	11.49	10.77	10.10	9.30	7.48	6.82	5.96	1.80	0	11.15	9.83	8.68	4.36	0	10.39	7.14	3.75
V_{90}	11.48	10.76	10.03	9.10	6.17	4.86	3.50	0	0	11.14	9.74	6.37	2.20	0	10.35	5.60	1.50

only used for one discharge current and the interval time for reading of discharge voltage was 1 s. After discharge of 10 s, each battery was placed on rest position for 10 s. Then, they were discharged by currents of $0.6 \times I$, namely 0.6×50 A, 0.6×100 A, 0.6×150 A, ..., and 0.6×850 A until reaching to final voltage of 6 V. Each battery was only used for one corresponding discharge current and the interval time for reading of discharge voltage was 1 s.

After collecting all data, we tried to use only one model for all data. But, training of the network took a very long time and the prediction errors were high and they were not acceptable. Therefore, we classified the data into three groups and used a separate model for each group as following:

(1) Model 1 was used for first 10 s discharge data, which it discharged under different constant currents (I).
(2) Model 2 was used for critical voltages of 30 s (V_{30}), 60 s (V_{60}) and 90 s (V_{90}) under different discharge currents ($0.6 \times I$).
(3) Model 3 was used for time of reaching to final voltage of 6 V ($t_{6\,\mathrm{V}}$) at different discharge currents.

It should be mentioned that the model 3 was trained by using of $\log(t_{6\,\mathrm{V}})$. Because, current of cold discharge has a sigmoid relation only with $\log(t_{6\,\mathrm{V}})$. The relationship between cold cranking Amps (CCA) and time of reaching to cutoff voltage of 6 V ($t_{6\,\mathrm{V}}$), and also cold cranking Amps (CCA) with $\log(t_{6\,\mathrm{V}})$ were shown in Fig. 1. As it is seen from Fig. 1, CCA has a exponential relation with ($t_{6\,\mathrm{V}}$) and a sigmoid relation with $\log(t_{6\,\mathrm{V}})$. Initial studies showed that use of sigmoid transfer function for model 3 as for other models (1 and 2) had more ability and lower prediction errors.

All of three models are used for one aim, which is ensuring some data in fastest time; they propel us to cold cranking behavior, according to international standards. It should be noted that accuracy of the ANN model can be improved further by increasing the number of neurons and layers, but sacrificing the computational speed and implementation simplicity. So, the achievable accuracy is compromise result, which is acceptable as far as the engineering point of view, for calculation of the CCA, is concerned.

The experimental data in training, prediction and validation sets for models 1, 2 and 3 were shown at Tables 1–3, respec-

Table 3
Experimental data for training, prediction and validation sets for model 3

Voltage (V)	Current (A)																
	Training set									Prediction set					Validation set		
	50	150	300	450	500	550	650	700	850	100	250	400	600	750	200	350	800
$\log(t_{6\,\mathrm{V}})$	3.497	2.715	2.281	1.968	1.908	1.845	1.681	1.568	0	2.878	2.401	2.000	1.771	1.515	2.484	2.176	1.176

tively. The prediction error was used as a tool for controlling of training. The model with lowest prediction error was used as final and optimum model. Table 4 shows the architectures and specifications of the optimized ANNs.

After training process of the each model, it was used for prediction of cold cranking behavior of the batteries at five different discharge currents in the prediction set as an internal validation. Fig. 2 shows variation of predicted data verses experimental data for model 1 in prediction set at discharge currents of (a) 100, (b) 300, (c) 400, (d) 650 and (e) 800 A. Variations of predicted voltages versus experimental voltages for model 2 in prediction set for discharge times of (a) 30 s, (b) 60 s and (c) 90 s were shown in Fig. 3. Fig. 4 shows the variation of predicted $t_{6\,\mathrm{V}}$ verses exper-

Table 4
Architecture and specification of the generated ANNs

Model	1	2	3
No. of nodes in the input layer	1	1	1
No. of nodes in the hidden layer	7	8	3
No. of nodes in the output layer	10	3	1
Learning rate	0.1	0.1	0.1
Momentum	0.1	0.1	0.1
Number of epochs	130000	60000	13000
Transfer function	Sigmoid	Sigmoid	Sigmoid

Models 1, 2 and 3 were used for cold cranking behavior at first 10 s of discharge, operation voltage at discharge times of 30, 60 and 90 and times of reaching to final voltage of 6 V, respectively. (No biases in input and output layer).

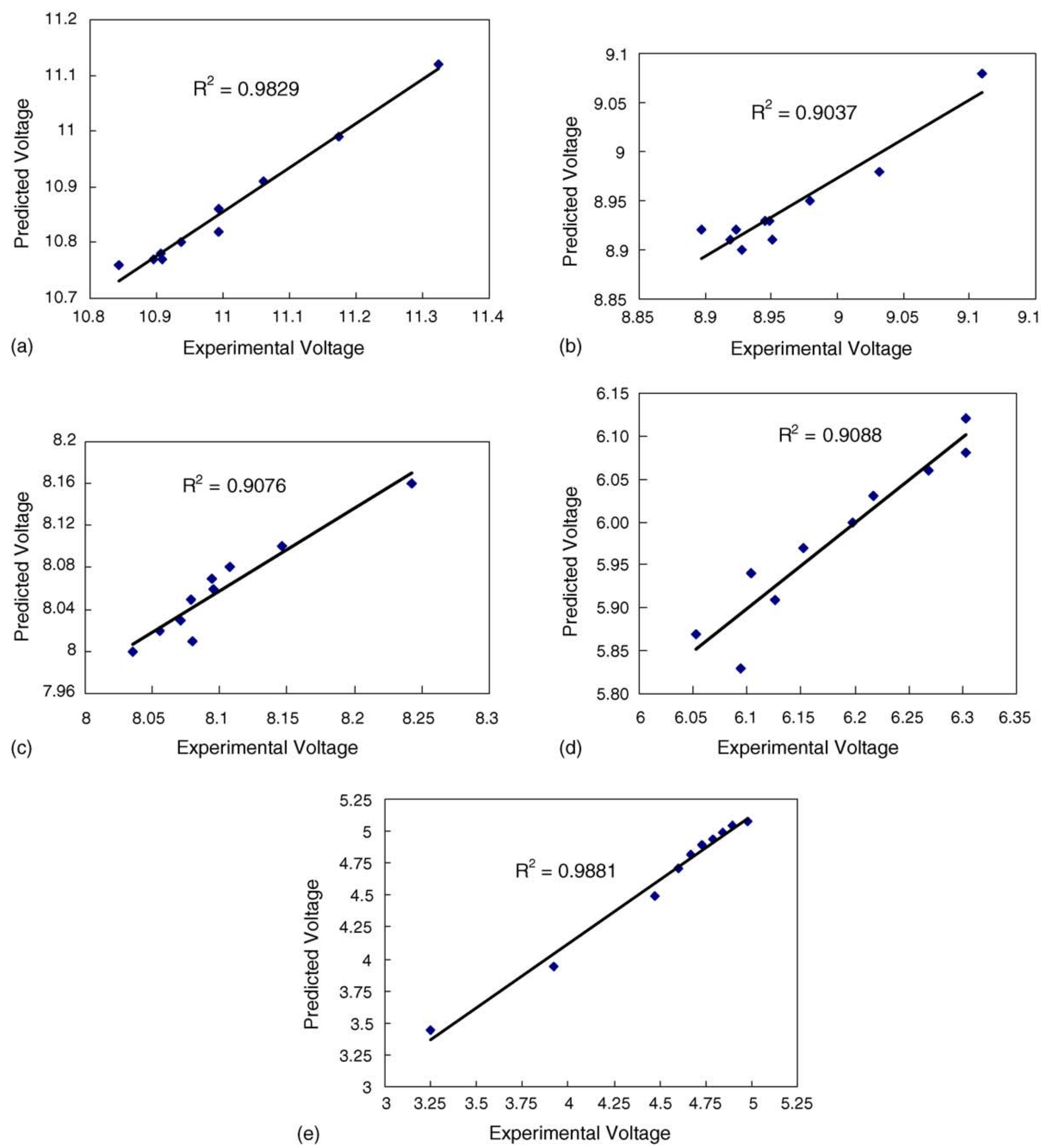

Fig. 2. Variation of predicted voltages vs. experimental voltages for discharge current of (a) 100 A, (b) 300 A, (c) 400 A, (d) 650 A and (e) 800 A for model 1 in prediction set.

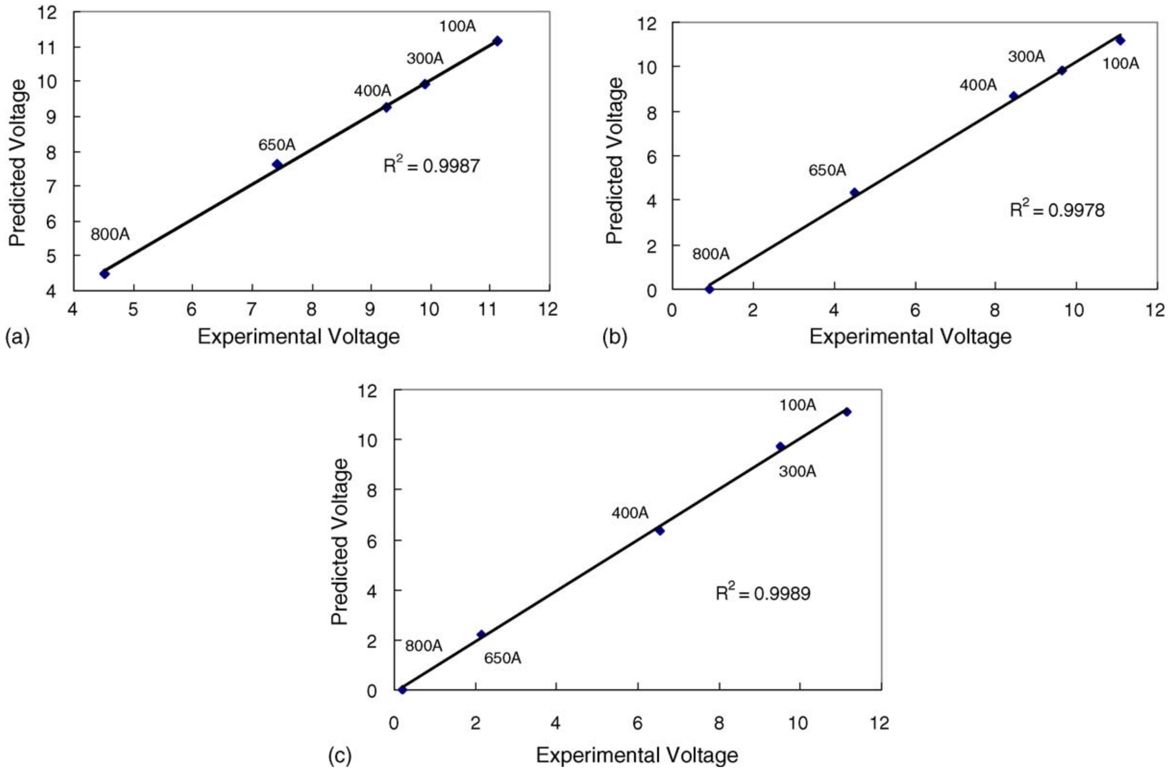

Fig. 3. Variations of predicted voltages vs. experimental voltages for model 2 in prediction set for discharge times of (a) 30 s, (b) 60 s and (c) 90 s.

imental $t_{6\,V}$ at different discharge currents. As it is seen from these figures, the prediction data has a good compatibility with the corresponding experimental data. Then, the models can be used with low prediction error for prediction of CCA.

After testing of the models by internal validation in prediction data set, the proposed models were tested by three different discharge currents in validation set as an external validation. Fig. 5 shows ability of model 1 in prediction of battery voltage during 10 s discharge at currents of 200, 500 and 750 A. As it is seen from Fig. 5, the predicted and experimental time–voltage behaviors of batteries during 10 s discharge at different discharge currents are very similar. Maximum prediction error was lower than 3.1%. Thus, the model 1 can be successfully used for prediction of time-voltage behavior during cold discharge and prediction of voltage at time of 10 s (V_{10}).

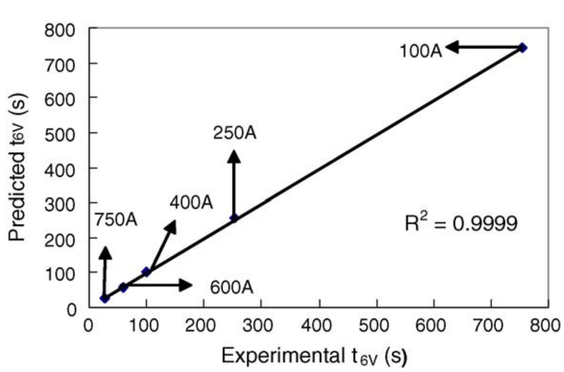

Fig. 4. Variations of predicted voltages vs. experimental voltages for model 3 in prediction set.

Model 2 was used for prediction of voltage at discharge times of 30, 60 and 90 s in validation set as an external validation. Amounts of predicted voltages at critical points (V_{30}, V_{60} and V_{90}) versus corresponding experimental values were plot in Fig. 6. As Fig. 6 shows, the model 2 is very useful and capable for prediction of critical voltage at cold cranking test. The prediction error for model 2 at maximum amount was lower than 3.3%.

Model 3 was employed for prediction of time of reaching to cutoff voltage of 6 V ($t_{6\,V}$). Sigmoid transfer function was used for successful modeling and prediction of $t_{6\,V}$. Fig. 7 plots the relation between predicted $t_{6\,V}$ and experimental $t_{6\,V}$ at validation set. As it is seen from this figure, model 3 can be successfully used for prediction of $t_{6\,V}$ at different cold discharge currents with prediction error lower than 3.5%.

Table 5 shows maximum prediction error in prediction and validation sets. As it is seen from Table 5, there is a good agreement between experimental data and predicted data. The prediction error of 10% or lower is acceptable for ANN models.

It is explicit that the three proposed ANN models exhibit a high accuracy for prediction of the CCA and they are not very demanding in computational effort; once the ANN model has

Table 5
Maximum prediction errors (%) of the proposed ANN models for prediction and validation sets

Model	1	2	3
Prediction set	5.59	3.46	1.55
Validation set	3.05	3.27	3.44

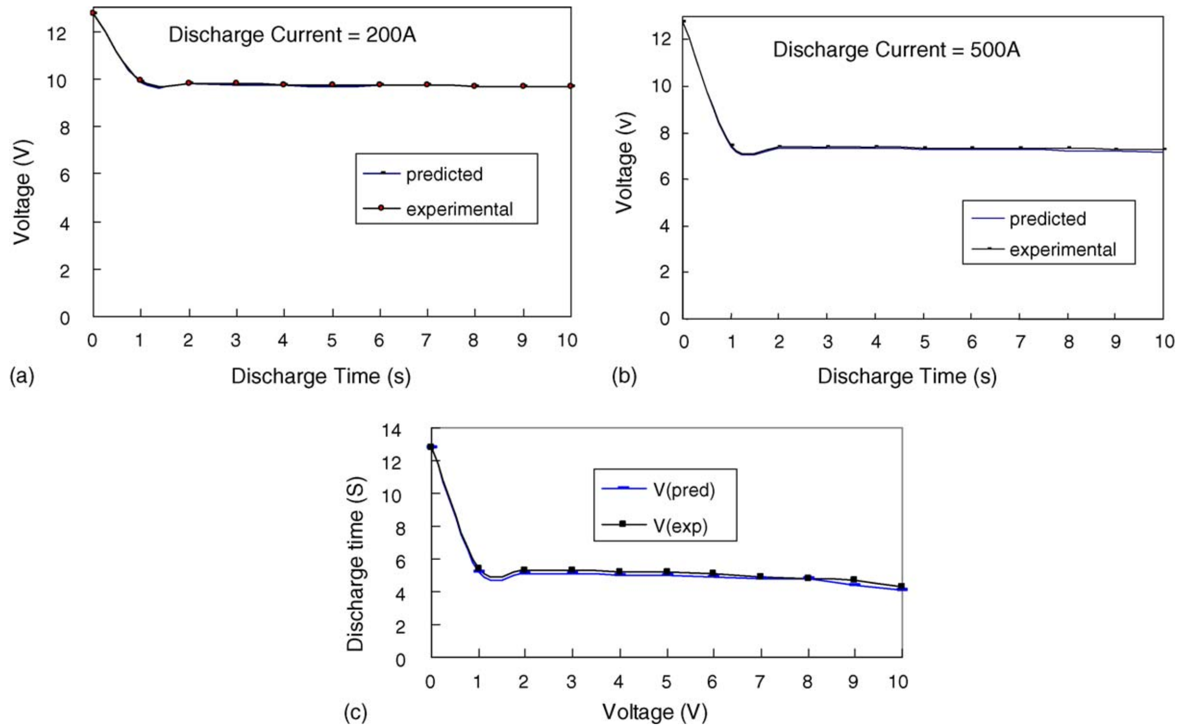

Fig. 5. Comparison of predicted time-voltage behavior and experimental data for model 1 at discharge current of (a) 200 A, (b) 500 A and (c) 750 A in validation set.

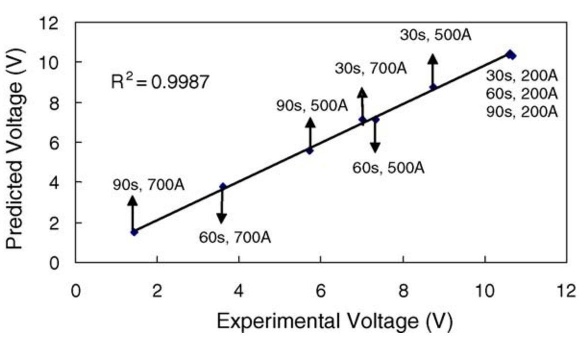

Fig. 6. Variation of predicted voltage vs. experimental voltage at different discharge currents and different discharge time for model 2 in validation data set.

been trained. The obtained results showed that the model can be used in battery industries for prediction of cold cranking behavior of the lead-acid batteries at high discharge current based on experimental cold cranking data at low discharge currents without using of expensive and complex instruments. Also, during

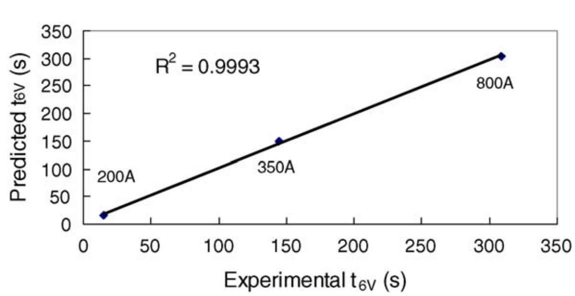

Fig. 7. Variation of predicted $t_{6\,\mathrm{V}}$ vs. experimental $t_{6\,\mathrm{V}}$ for model 3 in validation set.

the modeling process, the ANN model structure for calculation of CCA is independent of the lead-acid battery type, so the proposed modeling approach can readily be extended to all types of lead-acid batteries, provided that the corresponding experimental data are available for training an appropriate ANN model.

4. Prediction of suitable CCA for a battery

The final models were used in WinNN 32 for making a EXE file (a program for CCA Prediction) for inexpert operators in industries of lead-acid batteries in order to prediction of cold cranking behavior at high discharge currents and in order to prediction of suitable CCA for a battery based on experimental low discharge currents data as following:

The program retrains the models with new data corresponded to three or four low discharge currents, which have been carried out in the factory. Then, operator should experimentally check the battery behavior at four or at least three discharge currents (for example 50, 100 and 150 A), then he should train each model with these data. Finally, the operator checks the prediction of models for a proposed discharge current. Operator can input this discharge current as CCA based on guesswork, and the models predict the battery behavior with the input CCA. If the critical conditions of CCA corresponding to the acceptable standard of the factory are provided, the operator selects this discharge current as CCA. If the predicted amounts of critical points are lower than the factory standard, operator will input the lower discharge current into the models until to reach the highest discharge current which can provides the factory standard conditions. Fig. 8 shows the manner that an operator can predict suitable CCA for a lead-acid battery.

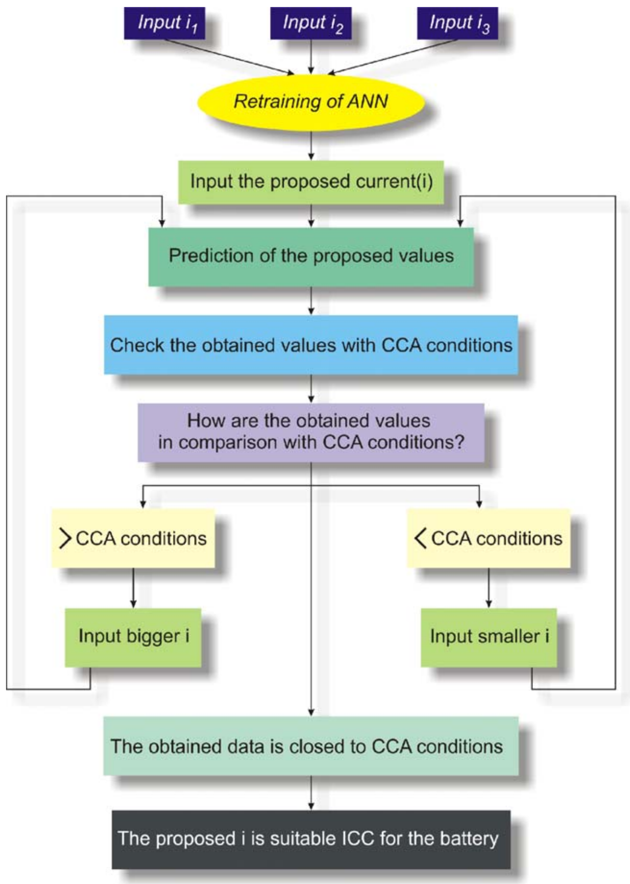

Fig. 8. The schematic manner for the determination of suitable CCA for a lead-acid battery.

5. Conclusions

Cold cranking behavior of lead-acid batteries can be modeled by artificial neural networks (ANNs). Three models were optimized for prediction of a complete CCA test. The models can be used successfully for prediction of time-voltage behavior during the first 10 s discharge with CCA, for prediction of critical voltages of 30 s (V_{30}), 60 s (V_{60}), 90 s (V_{90}) and for prediction of time of reaching to cutoff voltage of 6 V. The optimized models were used for making an EXE file (operating program) for use in quality control centers of lead-acid industries. The program can be used by inexpert operators for prediction of battery behavior at cold discharge of battery at a high current and or for determination of suitable CCA amount for a lead-acid battery based on data at low currents of cold discharge.

Acknowledgements

We gratefully acknowledge the support of this work by Aranniru battery Co., Payame-Noor University of Ardakan and Sepahan Battery Co.

References

[1] E. Karden, S. Buller, R.W. De Doncker, Electrochim. Acta (2002) 2347.
[2] E. Karden, S. Buller, R.W. De Doncker, J. Power Sources 85 (2000) 72.
[3] F. Huet, J. Power Sources 70 (1998) 59.
[4] J.B. Copetti, F. Chenlo, J. Power Sources 47 (1994) 109–118.
[5] P. Mauracher, E. Karden, J. Power Sources 67 (1997) 69.
[6] A.J. Salkind, C. Fennie, P. Singh, T. Atwater, D. Reisner, J. Power Sources 80 (1999) 293.
[7] A.J. Salkind, T. Atwater, P. Singh, S. Nelatury, S. Damodar, C. Fennie Jr., D. Reisner, J. Power Sources 96 (2001) 151–159.
[8] V. Viswanathan, A.J. Salkind, J.J. Kellery, J.B. Ockerman, Part II, lead-acid, J. Appl. Electrochem. 25 (1995) 729.
[9] P. Singh, C. Fennie Jr., D. Reisner, J. Power Sources 136 (2004) 322.
[10] C. Armenta-Deu, Renew. Energy 28 (2003) 1671.
[11] M. Thele, S. Buller, D.U. Sauer, R.W. De Doncker, E. Karden, J. Power Sources 144 (2005) 461.
[12] A.J. Salkind, P. Singh, A. Cannone, T. Atwater, X. Wang, D. Reisner, J. Power Sources 116 (2003) 174.
[13] H. Blanke, O. Bohlen, S. Buller, R.W.D. Doncker, B. Fricke, A. Hammouche, D. Linzen, M. Thele, D.U. Sauer, J. Power Sources 144 (2005) 418.
[14] C.C. Chan, E.W.C. Lo, W.X. Shen, J. Power Sources 87 (2000) 201.
[15] C. Yow Tseng, C. Lin, J. Power Sources 147 (2005) 282.
[16] D.O. Feder, M.J. Hlavac, S.J. McShane, J. Power Sources 48 (1994) 135.
[17] A. Urbina, T.L. Paez, C. O'Gorman, P. Barney, R.G. Jungst, D. Ingersoll, J. Power Sources 80 (1999) 30.
[18] O. Caumont, P.L. Moigne, C. Rombaut, X. Muneret, P. Lenain, IEEE Trans. Energy Convers. 15 (2000) 354.
[19] P.E. Pascoe, J. Power Sources 45 (2004) 1015.
[20] P. Hagan, D. Fellowes, J. Power Sources 122 (2003) 77.
[21] P.E. Pascoe, A.H. Anbuky, Energy. Convers. Mgmt. 45 (2004) 277.
[22] A.J. Salkind, C. Fennie, P. Singh, T. Atwater, D.E. Reisner, J. Power Sources 80 (1999) 293.
[23] W.X. Shen, C.C. Chan, E.W.C. Lo, K.T. Chau, Energy. Convers. Mgmt. 43 (2002) 817.
[24] M.T. Loponen, P. Jalas, J. Power Sources 30 (1990) 249.
[25] Iranian National Standard of Starter Lead-acid Batteries, No. 71, p. 12.
[26] IEC, 60095-1, Ed. 6, 2000-12, p. 17.
[27] Peugeot Standard Systems, C255210, 2000, p. 6.