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A systems approach for sizing a stand-alone residential PEMFC power system

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Abstract

Polymer electrolyte membrane fuel cells (PEMFCs) show great promise in portable, automotive, and stationary applications. They have reached the test and demonstration phase in automotive and power markets today. This paper is focused on a stand-alone residential PEMFC power system that provides the electricity needs of the house. A novel stochastic sizing methodology is developed that considers both fuel cell system dynamics and residential load dynamics in overall system sizing for the stand-alone residential fuel cell power system. Understanding the nature of demand side is critical in stand-alone system sizing. Thus, experimental measurements have been completed to capture the load side dynamics in detail. No such data is found in the current literature. The Threshold Bootstrap method is used to model the residential load demand and to produce many realistic load profiles. Matlab/Simulink is used to run system simulations to determine system sizes based on parameters defined through a designed experiment. Comparison between the proposed sizing method and a possible worst case scenario sizing is given. The new sizing methodology can be used together with sophisticated demand analysis programs to obtain customized sizing for each user as stand-alone power systems become more viable.

Keywords: Fuel cell; Residential load; Stochastic; Sizing; Power systems; Stand-alone

1. Introduction

Fuel cells are electrochemical reactors which realize the direct conversion of the chemical energy of the reactants to electrical energy, with high efficiency and high environmental compatibility [2]. Among the different types of fuel cells, 'Polymer Electrolyte Membrane Fuel Cells (PEMFCs)' show great promise in portable, automotive, and stationary applications because of their high power density, low operating temperature, zero pollutant emission and performance stability. They have a solid proton conducting electrolyte, light weight, compactness, short start-up time, and low cost. PEMFCs have reached the test and demonstration phase in automotive and power markets today [21–25].

This paper is focused on a stand-alone residential PEMFC power system that provides the electricity needs of a residential house. Although a fuel cell stack within the fuel cell system can deliver the requested power instantaneously as long as the required reactant flow rates are established, overall fuel cell systems have a delay characteristics to a transient condition in current demand [15–18]. The requested reactant flows for an increase in the current demand cannot be provided instantaneously due to mechanical components in the system, such as reformers and blowers. Thus, a backup source (such as a battery or supercapacitors) must be used to meet dynamic loads in the stand-alone system. Due to the time-delayed response of the fuel cell system, load dynamics become important in defining the size of the backup energy storage.

Since most of the load transients in a typical house happen on the order of cycles, high resolution load data is required for proper sizing analysis. The data reported in earlier sizing studies

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were mostly based on hourly averaged values of load demand, solar radiation and wind speed [8–10]. Thus, they do not provide the necessary detail that is important in the case of a stand-alone system. However, understanding the nature of residential load demand is critical for the stand-alone system sizing. The dynamics faced by the fuel cell system will be quite different when a single house is considered compared to a collection of houses. The importance of such dynamics is reported in [4–7]. However, no study has previously been completed for residential load modeling with the level of detail considered in this study.

In addition, the random nature of the load needs to be addressed in stand-alone system sizing. Thus, the sizing problem turns into a probabilistic sizing problem for a single house. The worst case scenario sizing used in the industry does not consider these details and generally oversizes the system. In this study, a novel approach is taken, i.e. both fuel cell system dynamics and detailed load dynamics are taken into account.

This paper is organized as follows: In Section 2, the need for high resolution load data and residential load modeling are explained. In Section 3, the dynamic fuel cell system model is given. In Section 4, a stochastic sizing methodology is introduced. Comparison with a possible worst case scenario sizing is given. In Section 5, conclusions are given.

2. Residential load modeling

When the grid is not present, details of the load profile become important in stand-alone system operation and sizing study. With a sizing study using hourly data, all information is lost within the hour interval, as shown in Fig. 1. Since the fuel cell system cannot respond instantly to an increase in current demand, these dynamics are important and will have implications for backup energy source size. The dynamic and random nature of the load demand must be taken into account in the stand-alone system. The importance of such dynamics is reported in Refs. [4–7]. However, no study has previously been completed for residential load modeling with the level of detail considered in this study.

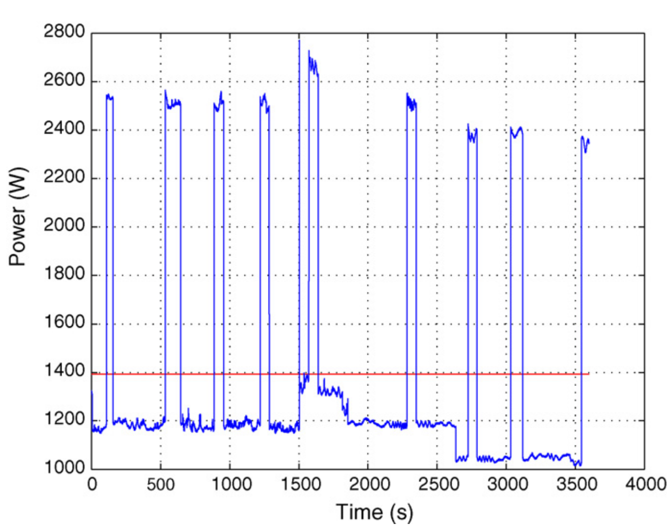

Fig. 1. Hourly averaged load profile (flat line) and dynamic load profile.

A high resolution demand profile must be obtained for proper sizing analysis. Therefore, experimental data have been collected for a residential house in Troy, NY, USA to capture the details of load dynamics. The data were taken in the winter and, thus, it could be assumed as the worst loading condition for the house. Current and voltage waveforms of the house are captured with a sampling rate of 1000 points per second, which provides us with a clear picture of residential load dynamics. No such data could be found in the literature. The Yokogawa DL 750 measurement device is used to capture the waveforms [26]. A 24-hour time period is captured to obtain a daily cycle for the house. The data is divided into hourly segments to make it easier to work with. Also, one period in a 60 Hz signal is combined into a single data point through averaging. This way data length is reduced by approximately 1/16. Depending on the time constant in fuel cell systems, one or more cycles can also be combined.

The collected data give us only one measured load profile. If the start time of the data collection or the pattern of appliance usage changed, one would not obtain the same time series. Due to the random nature of load behavior, there could be different loading patterns within the hour itself and most importantly each hour's data could result in a different backup size for given fuel cell system parameters. A solution to this problem is to collect more data for a longer time frame. However, obtaining more real life data is not only time consuming but impractical and will not cover all possibilities. Thus, a general methodology is needed to produce many realistic load profiles based on real data for a systematic analysis.

A statistical method, the Threshold Bootstrap (TB) [13,14], is employed for this purpose. The residential load is considered as a random process and the TB is used to convert a single sample into multiple realistic simulation input scenarios for system simulations. Applications of the TB in scenario generation are fully analyzed in Ref. [12]. In Refs. [11,12], producing simulation inputs from one historical trace is considered. The first formal visual inspection of bootstrap samples using the Turing test is completed [11] and it has been concluded that bootstrap samples are not visually distinguishable from real data. The TB is a modified version of the conventional bootstrap [3]. Rather than considering individual observations as in the conventional bootstrap, the TB considers 'cycles' as the resampling units. Considering a time series already obtained as in our case, the TB method works as follows (Fig. 2):

(1) Choose a threshold level (usually the mean or median).
(2) Divide the series into cycles created by the threshold.

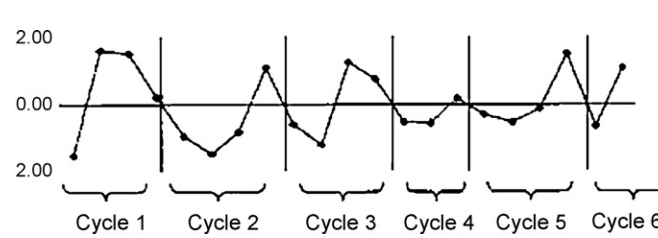

Fig. 2. Determination of cycles for a given time series [12].

(3) Create a bootstrap sample by concatenating cycles that are randomly selected from the set of all cycles.
(4) Truncate the new sample when the original data length is reached.
(5) Compute the statistic of interest from the bootstrap sample.
(6) Repeat 3–5 steps for new samples *n* times.

Limitations of the TB scenario generation could be given as

- The minimum and maximum of the produced data cannot become smaller or larger than the minimum and maximum of the original data.
- The produced data will not introduce new possibilities of appliance usage; rather, it will change the time that they are used.

Together, these points suggest that the TB will somewhat underestimate the worst case scenario. The value of the TB is that it augments a single sample time series by creating an unlimited number of realistic alternative samples. It allows us to include demand side dynamics in the sizing methodology for the first time [1]. As can be seen from Figs. 3–5 , the TB is effectively mimicking the actual data.

The process of stand-alone residential load modeling will always include an uncertainty due to random nature of the load behavior. Our goal here is to identify the problem and to give a possible solution. With increasing storage capacities and electronic metering applications, the characterization of a stand-alone house will be much easier in the future and more informed decisions can be made for stand-alone systems.

3. Dynamic fuel cell system model

The principle of electricity generation from the PEMFC is straightforward when the correct material properties, cell structure, and reactants (hydrogen and oxygen) are in place. The fuel cell system transient response, however, is limited by air flow, pressure regulation, heat, and water management [20]. As stated earlier, the fuel cell stack in the fuel cell power system will deliver the requested current as long as the necessary reactant flows that correspond to the required current are maintained. The down transients in current demand could be supplied without any delay since the reactant flows are already established for the higher power demand earlier. However, the up-transients in current demand will require a time delay. The chemical reaction within the fuel cell stack is extremely fast and can be assumed

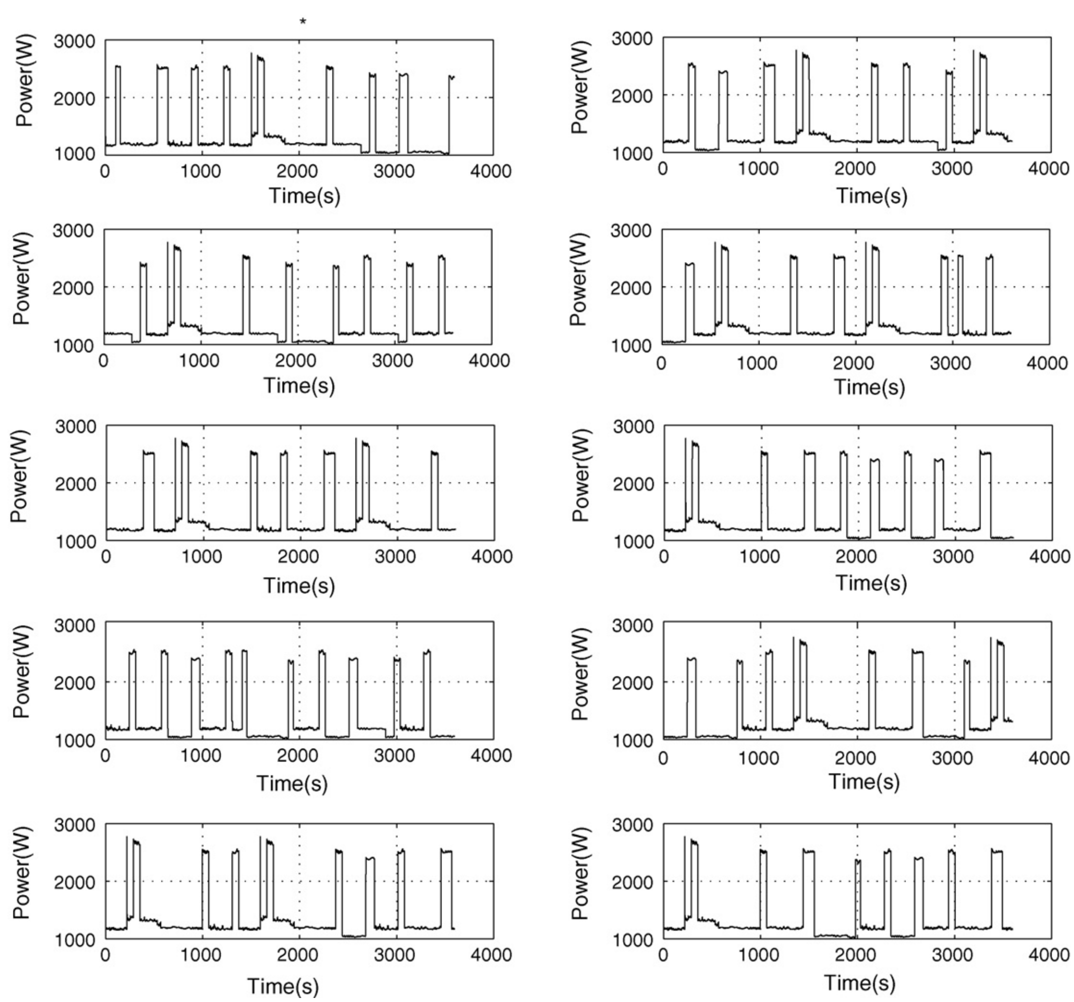

Fig. 3. Bootstrap data and actual data from 21:30 to 22:30 Actual data are shown on the top left.

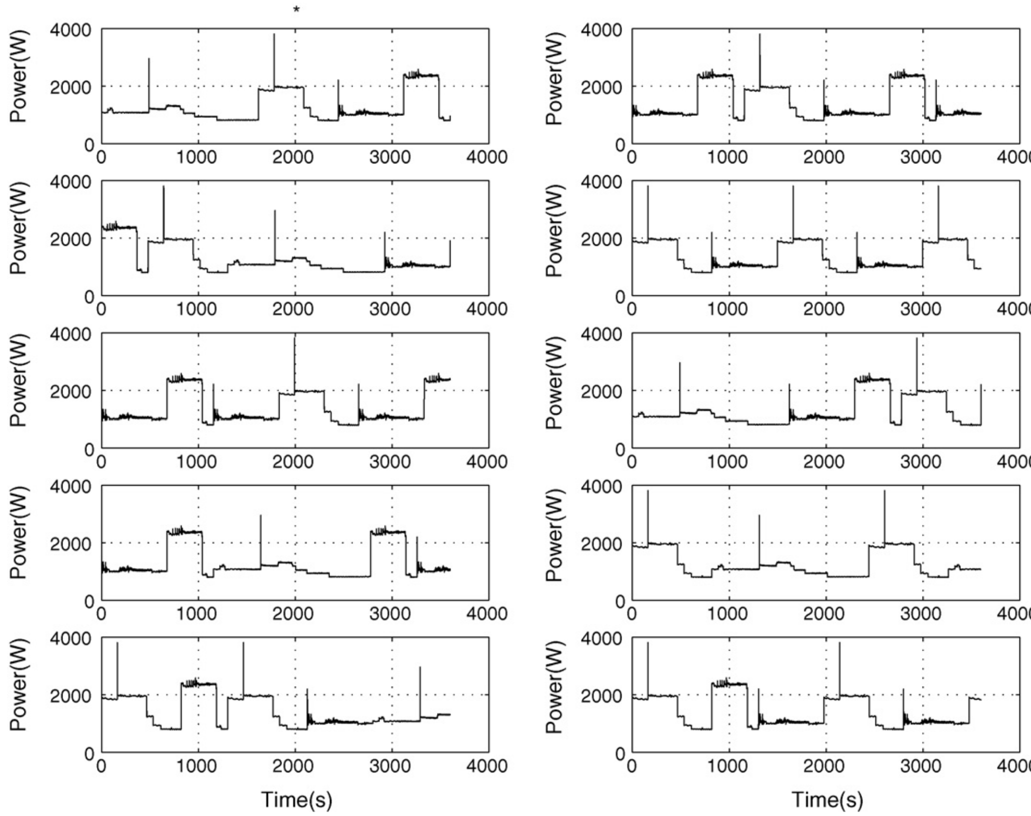

Fig. 4. Bootstrap data and actual data from 18:30 to 19:30 Actual data are shown on the top left.

instantaneous [20]. During a transient in current demand (especially an increase), both hydrogen and oxygen flow rates must be increased since the flows are directly related to the desired current. However, this cannot be completed without time delays due to the reformer, compressor or blower time constants in the mechanical systems. This is important in load-following applications, such as the stand-alone residential fuel cell system where load fluctuations are frequent. The time delay characteristics of the system have implications for overall system sizing.

A first-order time delay approximation is used to model the fuel cell system response to transients. In the literature, first-order time delay approximations for the fuel cell system are reported in several papers [15–18]. The assumption is verified using the experimental result for a real fuel cell system reported in Ref. [19]. The data given in Ref. [19] shows the response of the fuel flow to a step change in its control. The fuel cell flow rate is directly proportional to the current ($H2_{\text{flow}} = I/2F$). The experimental data and the first-order approximation results are plotted together to compare our first-order assumption with the real life data (Fig. 6). As can be seen, the first-order delay approximation closely follows the experimental data.

In the system sizing methodology, different power levels need to be considered. Therefore, a simple yet sufficiently accurate model of the fuel cell system is needed for fast simulation. The first-order delay assumption in the fuel cell system dynamic response offers this flexibility while not losing the necessary dynamics for the system simulations.

4. Stochastic sizing methodology for the stand-alone residential fuel cell power system

Both load dynamics and fuel cell system dynamics are taken into consideration in the following methodology, which has been used to determine the size of backup for a house with a given load profile, fuel cell system maximum power, and fuel cell system time constant.

- The residential load data is considered to be a random process and the Threshold Bootstrap (TB) method is used to produce multiple input scenarios based on the actual data for system simulations.
- The fuel cell system time constant, fuel cell system maximum output power, and backup size are considered to be our design parameters (τ, P_{cellmax}, E_{backup}). Minitab statistical software is used to develop a Box-Behnken response surface experimental design for three design parameters. Fifteen design points are obtained.
- System simulations are run for each design point with 250 new load profiles obtained using the TB. The block diagram of the simulation is shown in Fig. 7. The difference between fuel cell system output power and load power defines the power drawn from the backup and used to calculate the backup state of the charge (SOC).
- The SOC is used to define the reference power (P_{ref}) that will drive the dynamic fuel cell system model (Eq. (1)). $\text{SOC}_{\text{limit}}$ is the minimum SOC allowed before charging starts. It is a

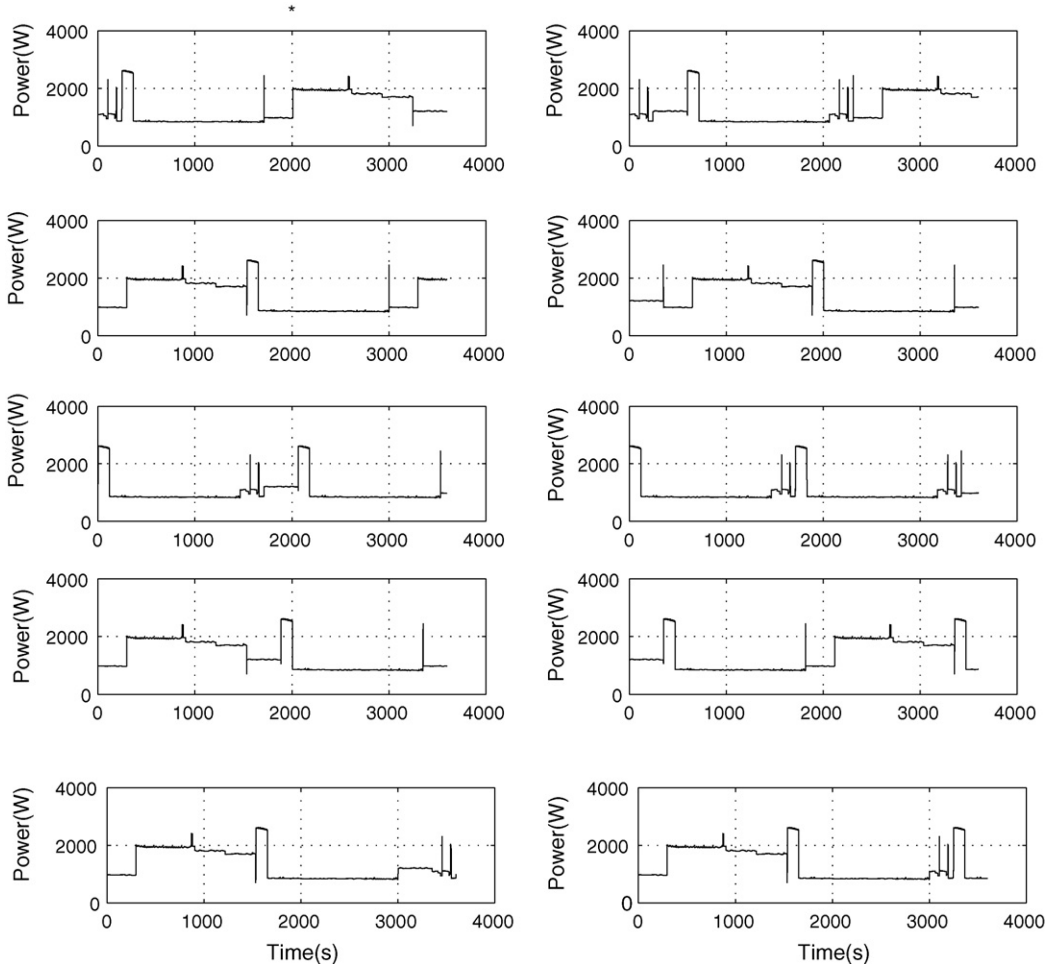

Fig. 5. Bootstrap data and actual data from 14:30 to 15:30 Actual data are shown on the top left.

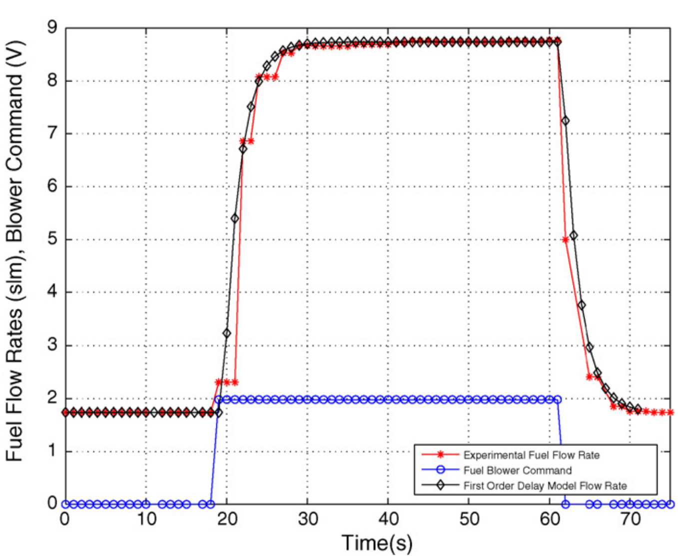

Fig. 6. Verification of the first-order delay assumption with experimental data [19].

user defined parameter and taken as 40% in our study.

$$P_{\text{ref}} = \begin{cases} P_{\text{load}} & \text{if SOC} = 1, & x=0,\ \text{discharge} \\ P_{\text{load}} & \text{if SOC}_{\text{limit}} < \text{SOC} < 1, & x=0,\ \text{discharge} \\ P_{\text{cellmax}} & \text{if SOC}_{\text{limit}} \leq \text{SOC} < 1, & x=1,\ \text{charge} \\ P_{\text{cellmax}} & \text{if SOC} < \text{SOC}_{\text{limit}}, & x=1,\ \text{charge} \end{cases} \tag{1}$$

- Average state of the charge (SOC_{ave}) is recorded at each design point. Thus, a matrix with 1×250 dimension is obtained for every design point.
- The probability of SOC_{ave} staying bigger than a user-selected threshold value SOC_{th} ($p(\text{SOC}_{\text{ave}} > \text{SOC}_{\text{th}})$) is calculated

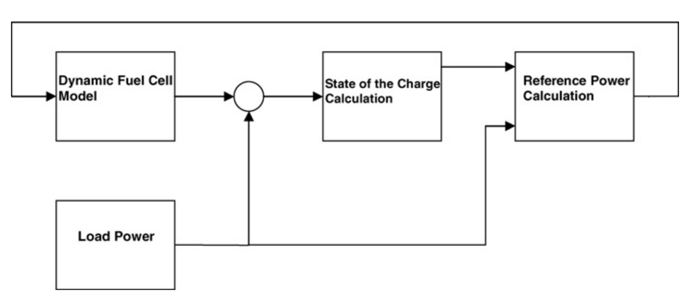

Fig. 7. Block diagram for system simulations.

Table 1
Design parameters

$P_{cellmax}$ (W)	1500–2500
τ (s)	1–15
E_{backup} (J)	$3 \times 10^5 - 1 \times 10^6$

from simulation results and used as the response column in Minitab Design of Experiments (DOE) analysis. The relationship between the response ($p(SOC_{ave} > SOC_{th})$) and design parameters ($P_{cellmax}$, τ, E_{backup}) are found. Contour plot is used to select both backup energy source size and fuel cell system size.

- New 250 load profiles are produced using the TB in order to check the selected sizes. Simulations are run for the selected points to check if the condition for the selection is satisfied.
- The backup size found through new sizing methodology is compared with a possible worst case scenario sizing. The worst case scenario is obtained by superimposing the experimental measurement of individual appliances voltage and current waveforms.

4.1. Results

The three design parameters and their ranges used in the Minitab software are given in Table 1. Average state of the charge for each load profile at each design point is recorded for high load hours (14:30–18:30–20:30–21:30) for the considered house. The SOC_{th} is chosen to be 60%. Therefore, the response is given as $p(SOC_{ave} > 0.60)$. The low load hours are not included in the analysis since during those hours, the SOC does not deviate much from the target value of 100% for any design points considered.

The relationship between the response ($p(SOC_{ave} > 0.60)$) and design parameters ($P_{cellmax}$, τ, E_{backup}) are found using Minitab. The model obtained through Minitab analysis has a $R - \text{Sq} = 98.9\%$ and $R - \text{Sq}(adj) = 97\%$ which means that 97% of the variations in the data can be explained by the model. The plot of response versus fitted values is given in Fig. 8.

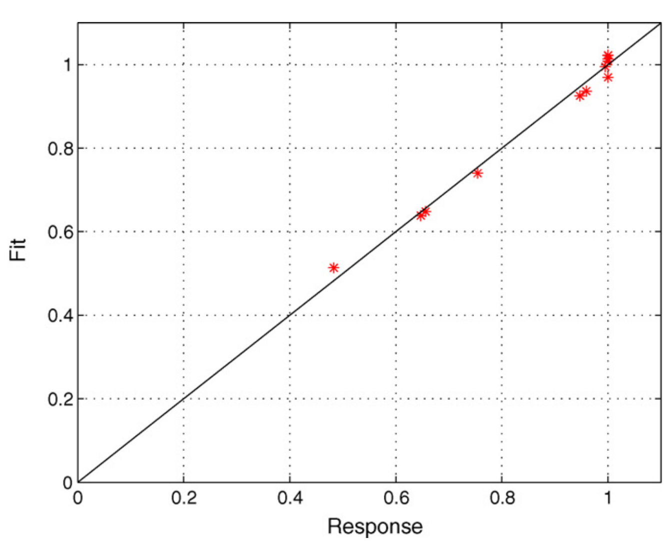

Fig. 8. Actual response vs. fitted data.

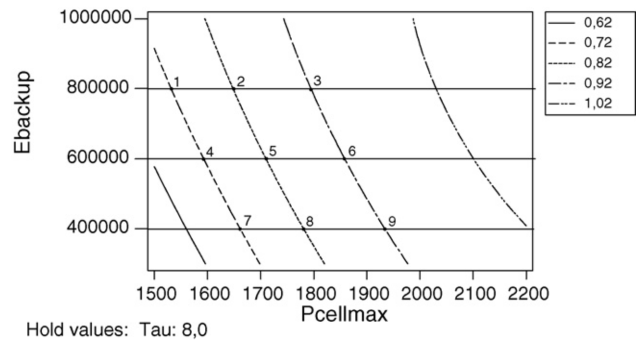

Fig. 9. $P_{cellmax}$ vs. E_{backup} for a fixed τ.

Minitab also provides contour plots to visualize the relationships. The contour plots provides visual reference about the effect of two design parameters on the response variable while one of the design parameters is kept constant. The relationship between E_{backup} and $P_{cellmax}$ for a fixed time constant is shown in Fig. 9.

The curves in Fig. 9 show different probability lines to meet the load demand. Failure to meet load demand probabilities can also be obtained from these curves as a function of both $P_{cellmax}$ and E_{backup}. As an example, a point chosen from 92% probability line means at least 92% of the time (out of 1000 simulated cases) SOC_{ave} will be bigger than 60%. Hourly simulation results are used to decide whether the selection criteria is satisfied or not. The criteria to meet the load demand defined as the probability of average state of the charge staying bigger than 60% for each high load hours. The failure to meet demand probabilities can be obtained by subtracting the probability of meeting the demand values from 100%. When a point from 92% probability line is chosen, then corresponding $P_{cellmax}$ and E_{backup} values will 8% of the time fail to meet demand.

The sizing curves in Fig. 9 can also be used for tradeoff analysis in cost saving versus penalty since they provide information about both costs (indirectly) and failure probability. As an example, although point 1 has a lower system cost compared to point 2, it has higher failure probability compared to point 2.

This plot is used to select fuel cell system power ($P_{cellmax}$) and backup size (E_{backup}) for points 1–9 shown in Fig. 9. Points 1, 4, and 7 are selected from 72% probability line; points 2, 5, and 8 are selected from 82% probability line; and points 3, 6, and 9 are selected from 92% probability line. Corresponding $P_{cellmax}$ and E_{backup} values for each point are given in Table 2.

Once sizes are selected for each point using the sizin curves in Fig. 9, system simulations are run for validation purposes with 250 new scenarios obtained using the TB. Obtained probability values are summarized in Fig. 10. As can be seen, the probability to meet the load demand criteria is satisfied for all chosen points.

Failure to meet load demand probabilities for different backup sizes using the results of simulated cases for points 1–9 are shown in Fig. 11.

It should be noted that the selected $P_{cellmax}$ and E_{backup} values are only a starting point and might not satisfy the selection

Table 2
$P_{cellmax}$ and E_{backup} values for the selected points shown in Fig. 9

Points	1	2	3	4	5	6	7	8	9
$P_{cellmax}$ (W)	1,533	1,647	1,794	1,594	1,715	1,857	1,666	1,782	1,936
E_{backup} (J)	800,000	800,000	800,000	600,000	600,000	600,000	400,000	400,000	400,000

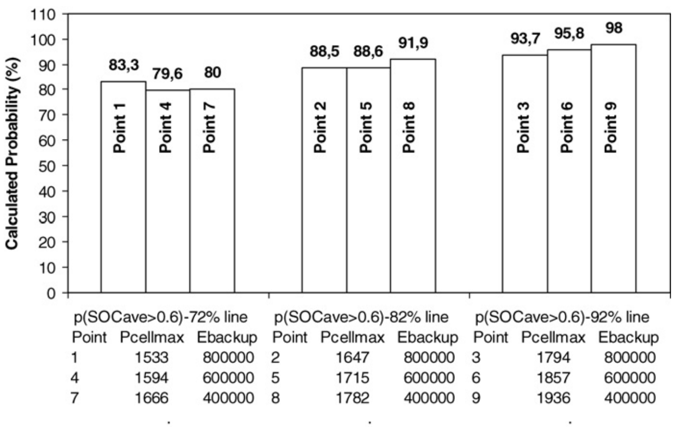

Fig. 10. Obtained probabilities to meet the load demand ($p(SOC_{ave} > 0.60)$) for the selected points (1–9) through simulations.

criteria. Since the problem is stochastic in nature, the results obtained will not be the exact answer. The results from the DOE can be used as a starting point for a final solution. The DOE reduces the search space for the solution since the analysis gives us an estimate of where the solution could be for different design parameters. Then, a more refined local search can be used to reach a final solution.

4.2. Comparison with a worst case scenario sizing

In order to compare the results of the sizing method introduced here with the worst case sizing, a possible worst case for the considered house is obtained by superimposing the individual appliance profiles. The considered appliances, that are commonly seen in a residential house, are

- Oven and oven-top
- Microwave
- TV
- Living room lights
- Garage door opener
- Refrigerator
- Vacuum cleaner
- Dryer
- Washing machine
- Toaster
- Dishwasher

Each appliances current and voltage waveforms are measured experimentally using the DL 750. The rms values of both current and voltage waveforms are used to calculate power requirements. The dishwasher cycle was the longest among all the appliances. Therefore, its running time is considered as the stopping time. The superimposed load profile is shown in Fig. 12.

During the first minutes of the cycle, the power requirement is quite high since all the appliances mentioned above are being used. However, the power requirement goes down as time progress since some of the appliances are off one by one. For example, the refrigerator is on with its periodic on and off times for the duration of the cycle while the garage door opener is operating only once at the beginning of the cycle. TV and living room lights are on for the duration of the cycle as well. Washing machine and dryer are used for one loading. Microwave is operated to heat up a dinner plate while vacuum cleaner and toaster are operated approximately 5 min. Oven was on for the duration of the cycle while oven-top was on for half of the cycle.

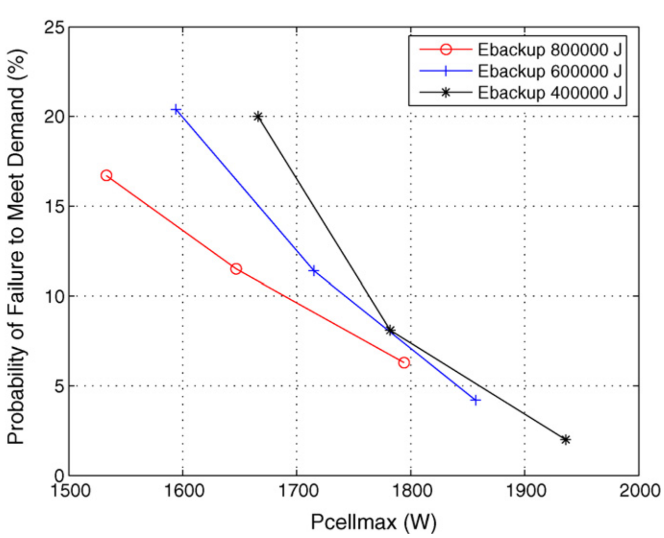

Fig. 11. Probability of failure to meet demand vs. $P_{cellmax}$ for different backup sizes using the results of simulated cases for points 1–9.

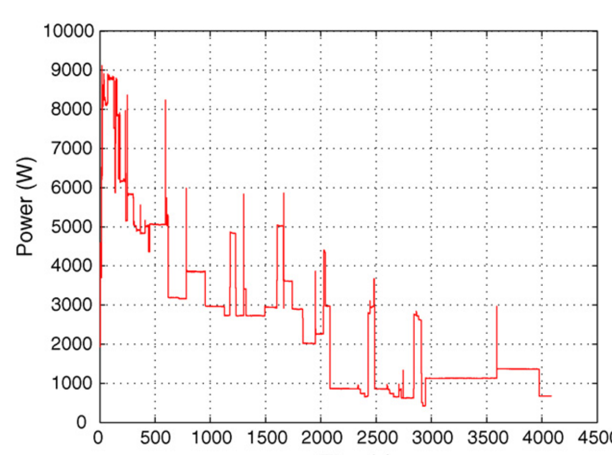

Fig. 12. A possible worst case loading scenario for the considered house.

Table 3
Comparison of the required energy backup values for the worst case sizing and the proposed sizing method for selected points 1–9

Points	$P_{cellmax}$ (kW)	Proposed method E_{backup} (kWh)	Worst case E_{backup} (kWh)
1	1532	0.222	2.972
2	1647	0.222	2.861
3	1794	0.222	2.694
4	1594	0.167	2.916
5	1715	0.167	2.777
6	1857	0.167	2.638
7	1666	0.111	2.833
8	1782	0.111	2.722
9	1936	0.111	2.527

The required energy backup for this worst loading case is calculated using the obtained worst case load profile as the input to our system simulation. For the same parameter values of selected points (Table 2), the required backup values to keep the SOC_{ave}above 60% are given in Table 3.

The results confirm our expectation that the worst case scenario sizing is dramatically oversizing the required backup for given fuel cell parameters. They also confirm the importance of both fuel cell systems dynamics and load dynamics in stand-alone power systems sizing.

5. Conclusions

A stand-alone residential fuel cell power system sizing is investigated in this study. A stochastic sizing methodology is introduced. Both load dynamics and fuel cell system dynamics are considered, as has not been done in the literature. The load side dynamics are captured in detail experimentally. The measured data, then, are used as basis for the Threshold Bootstrap to produce many realistic load profiles for a systematic sizing study. When the dynamics are considered, the required backup size is considerably reduced compared to typical worst case scenario sizing.

Since the sizing problem is stochastic in nature, the results obtained here will not be the exact answer. The methodology used cannot guarantee 100% coverage since it is impossible to do so. The randomness of the data profile and the path dependence of the sizing problem make it difficult to generalize the sizing methodology. However, the results from the DOE can be used as a starting point for a sizing solution. The DOE reduces the search space for the solution since the analysis gives us an estimate of where the solution could be for different design parameters. Then, a more refined local search can be used to find the final solution.

The sizing methodology given in this study could be used by setting other reliability standards, such as minimizing the total time of failure to meet the demand, for example 5 min total time of failure to meet demand out of 24 h. Total time of failure can be determined using the backup state of the charge. The duration that the state of the charge staying lower than a user-selected lower limit, such as 30% will provide the failure time. The summation of these durations will provide the total time of failure. Then, the total time of failure or its probability can be used as response variable in the DOE analysis and new sizing curves can be obtained.

Since 100% coverage cannot be guaranteed in the stand-alone operation without an overdesign as in the worst case scenario sizing, a load management algorithm to prevent a failure (no electricity) should be implemented in such a way that if the load is already at the limit of the system, the user could not start any other appliance or some of the loads could be taken out from the system. The requested demand could be satisfied at a later time. These preventive measures could be easily integrated into old buildings as well.

Cost is not considered in this study since the size and the cost relationship is linear in the stand-alone operation. The total cost of the system is the combination of both fuel cell system cost and backup energy source cost. Thus, any decrease in either fuel cell system size or backup size will lower the total cost. Under present economics, the fuel cell system is the most expensive part in overall system cost.

The sizing methodology given here can be used together with sophisticated demand analysis programs to compute a customized sizing for each user as the renewable energy sources becomes more affordable and more modular in the future.

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