# A Novel Demand Side Management Program using Water Heaters and Particle Swarm Optimization

Arnaldo Sepulveda, Liam Paull, Walid G. Morsi, Howard Li, C. P. Diduch and Liuchen Chang

Department of Electrical and Computer Engineering, University of New Brunswick, Fredericton, New Brunswick E3B 5A3
arnaldo.sepulveda@unb.ca, liam.paull@unb.ca, wmorsi@unb.ca, howard@unb.ca, diduch@unb.ca, and LChang@unb.ca

***Abstract*—Power systems' operators have the task of maintaining the balance between the demand and generation of electric power. Much research and attention is being given to find more environmental friendly sources of power generation. Naturally, more power is required when the load is at its peak value, and this tends to be when the most non environmentally friendly sources of power generation are used. This paper proposes a new controller for peak load shaving by intelligently scheduling power consumption of domestic electric water heater using binary particle swarm optimization. Past studies show that similar demand side management programs were not successful because the impact that the load control has on the end users' comfort. In this study, Binary Particle Swarm Optimization (BPSO) finds the optimal load demand schedule for minimizing the peak load demand while maximizing customer comfort level. A simulation in Matlab is used to test the performance of the demand response program using field data gathered by smart meters from 200 households. The direct load control is shown to be an effective tool for peak shaving of load demand, shifting the loads to valleys and reducing the aggregated load of electricity without compromising customer satisfaction.**

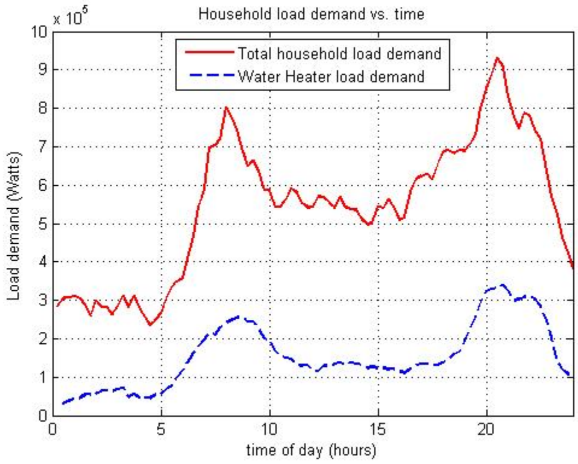


Fig. 1. Aggregated household load demand and aggregated water heater demand from field data from 200 households

## I. Introduction

The efficiency of the power grid is of great importance as environmental concerns related to the combustion of fossil fuels increase. One important way to reduce losses and increase power system stability is through advanced control algorithms on the load side. This idea is broadly referred to as Demand-Side Management (DSM). Different objectives have been considered by past DSM programs found in the literature, such as peak shaving and valley filling [1], and providing ancillary services like synchronous reserve [2], frequency regulation [3], and voltage stability [4].

Domestic electric water heaters (DEWH) are ideal candidates for DSM projects because the hot water in the tanks acts as an energy storage. In winter-dominated climates, the DEWH loads can contribute to as much as 30% of household load. In addition, the DEWH load profile and average daily load profile follow the same pattern, meaning that DEWH loads significantly contribute to peak load values [5]. Fig. 1 shows the aggregated total household load and the aggregated electrical water heater load for a typical day.

Using direct load control (DLC), it is possible to shift the load of the DEWH to the valleys of the daily load profile, resulting in a more constant load throughout the day. Power utilities pay a premium for monthly and daily peak values so if these can be reduced, there are significant savings which can help reduce cost to the customers.

Historically, many DSM programs fail not because they do not have technical benefits, but because there is too large of an impact on users for widespread acceptance. Therefore, it is necessary to consider very carefully the temperature of the water in the users' tanks so that comfort constraints are not violated.

Many DLC strategies have been proposed to control DEWH loads. In [6], a power management program for peak shaving is proposed by voltage control. In [7], a load shedding controller is proposed. In [8], a linear programming model is proposed for reduction of peak load demand.

Some researchers have considered the problem as an optimization and tried to maximize customer satisfaction. In [9], a framework for evaluation of advance direct load control with the objective of minimizing customer discomfort was developed. In [10], a customer centered load control strategy in demand response programs was proposed. In [11], a setpoint control strategies for reduction of peak load and energy cost was proposed. In [12], a multiobjective controller for peak load reduction was developed.

The approach considered in this paper is to use Binary Particle Swarm Optimization (BPSO) which was first proposed by Kennedy and Eberhart [13] as an extension of Particle Swarm Optimization (PSO) [14]. In PSO the use of agents

2010 IEEE Electrical Power & Energy Conference
978-1-4244-8188-0/10/$26.00 ©2010 IEEE

that interact with one another result in an intelligent system which learn from their experiences to search for a solution. Others have used PSO to schedule load demand in the past. In [15], a program to schedule demand side resources by BPSO is proposed. In [16], a load control approach to interrupt loads by PSO is proposed. The success of BPSO to find a solution to discrete space problems compared to continuous ones make BPSO a more capable tool for load management of DEWH. The frameworks presented in these past works are used here to develop a robust and real-time controller that can produce actual quantifiable peak shaving results.

To the knowledge of the authors this study is the first to use BPSO to schedule DEWH loads in a DSM program and achieve realistic results.

## II. Background and Related Work

The control methodology presented in Section III uses the theory of water heater models and binary particle swarm optimization that is presented here.

### A. Water Heater Model

In order to effectively control domestic electric water heater loads with minimum impact on residential customers, the water heater load and the temperature of the water in the tanks must be predicted. As described in [17], this is done using a developed non-aggregated water heater load model. In the current system, smart meters record household load on a 15-minute interval. First, the data must be processed in order to extract the water heater load from the household load. This is accomplished using a robust pattern recognition system that uses the known value of the water heater element (in this case 3kW). From test data, the amount of time that the element is required to be on to heat the water in the tank to the maximum temperature setpoints can be determined. The pattern recognition system can scan the data for 3kW loads that are on for the predetermined amount of time. Once the water heater load has been extracted from the household load, the next step is to determine the temperature of the water in the tanks in real-time so that user comfort is not compromised. This is accomplished using a previously established thermal model [18]. The thermal model is found by solving a differential equation and is given as:

$$
\begin{aligned}
T_H(t) \;=\;& T_H(\tau) e^{-(\frac{1}{R'C})(t-\tau)} \\
& + \{GR'T_{out} + BR'T_{in} + QR'\} \\
& \times \left[1 - e^{-(\frac{1}{R'C})(t-\tau)}\right] \qquad (1)
\end{aligned}
$$

where $\tau$ : initial time (hr);
$T_H(\tau)$ : initial temperature (°F);
$T_{in}$ : incoming water temperature (°F);
$T_{out}$ : ambient air temperature outside tank (°F);
$T_H(t)$ : temperature of water in tank at time $t$ (°F);
$Q$ : energy input rate as a function of time (W);
$R$ : tank thermal resistance ($m^2 \cdot$ °F/W);
$SA$ : surface area of tank($m^2$);
$G = SA/R$ (W/°F);
$W_D$ : water demand (L/hr)
$C_p$ : specific heat of water (W/(°F·kg))
$D$ : density of water = 1 kg/L
$B$ : $D \cdot W_D \cdot C_p$ (W/°F);
$C$ : (volume of tank)·(density of water)·$C_p$ (W/°F);
$R' = 1/(B + G)$ (W/°F);

This model is capable of determining the temperatures of the water in the tank for any given time all the parameters are known. The value of $\tau$ must be reset to zero when the value of either the input energy $Q$ or the water demand $W_D$ changes. The value of the input energy is determined by the extraction method described above. The water usage is predicted using a large amount of past data to develop a water usage profile. The water usage profile is also very useful in determining what times during the day the user is more likely to use water, and therefore it is important that the water in the tank be at an acceptable level at those times.

### B. Particle Swarm Optimization

Particle swarm optimization (PSO) is an optimization technique based on collaborative population introduced by Kennedy and Eberhart [14]. PSO was inspired by the social behaviour of animals such as flocks of birds. The behaviour of each individual in the population is represented by randomly initialized particles called swarms. These particles move through the multi-dimensional search space by updating their velocity and position from:

$$
\begin{aligned}
v_i{}^{(t+1)} \;=\;& w \cdot v_i{}^{(t)} + c_1 \cdot rand_1() \cdot (x_{Pbest,i}{}^{(t)} - x_i{}^{(t)}) \\
& + c_1 \cdot rand_2() \cdot (x_{Gbest,i}{}^{(t)} - x_i{}^{(t)}) \qquad (2)
\end{aligned}
$$

$$
x_i{}^{(t+1)} = x_i{}^{(t)} + v_i{}^{(t+1)} \qquad (3)
$$

where $v_i$ is the velocity of the particle; $w$, $c_1$, and $c_2$ are the momentum, personal acceleration and social acceleration constants respectively; $rand_1()$ and $rand_2()$ are two uniform random number generators; $x_i$ is the position of the $ith$ particle; $x_{Pbest,i}{}^{(t)}$ is the best position that the $ith$ particle has obtained from the objective function evulation; $x_{Gbest,i}{}^{(t)}$ is the best position obtained by all particles. Particle velocities are clamped between $-Vmax$ to $Vmax$. Once the total number of iterations is reached, the global best is the solution of the optimization problem.

Particles movements are affected by their history of best personal experience $Pbest$ and best global experience $Gbest$. The performance of particle positions is evaluated by a fitness function which is minimized by the PSO algorithm. If a particle has obtained a better position then $Pbest$ is updated; if a better global particle position is obtained then $Gbest$ is updated.

For discrete optimization problems Kennedy and Eberhart propose a binary version of the PSO (BPSO) [13]. In BPSO the particle populations are either 0 or 1, and the sigmoid function given by (4) maps the velocity values between 0 and 1.

$$S(v_i) = \frac{1}{1+e^{-v_i}} \tag{4}$$

Particle position is updated into a discrete space by comparing them to a random number between 0 and 1 as given by:

$$if(rand_3() < S(v_i)),\ then\ x_i = 1; \quad else\ x_i = 0. \tag{5}$$

## III. Proposed Control of DEWH

Peak load demand accounts for only a small portion of the generation capacity. However, this demand increases the stress on power systems and the total cost of electricity generation. Flattening the load profile can increase the power system efficiency and stability. Demand side management (DSM) programs are used to achieve this goal among others. DSM programs intentionally influence the energy use of the customers by controlling appliances from the utility side. Different desired load profiles can be used by the utility to achieve different objectives, such as: peak shaving, valley filling, and load shifting.

DLC is the process of controlling appliances either from the residential consumer side or the utility side. A DLC program can help to maintain the balance between generation and load by providing load shedding. Peak load demand of households and DEWH from field data collected by Saint John Energy from 200 households is shown in Fig. 1, their average temperature and aggregated water heater load in Fig. 2. It is noted that the profiles of the household load demand and the water heater load demand follow a very similar shape. This factor, combined with the DEWH's inherent energy storage capabilities, make the DEWH an ideal candidate for DLC in a DSM project. DEWH are controlled with wirelessly controlled relays at the load site. Smart meters are also installed at the household to record household electric load. The combination of the smart meters and the load control devices provides a fast and reliable two-way communication system.

A PSO based centralized controller for DLC of DEWH is proposed, as shown in Fig. 3, to minimize aggregated peak load demand, increase equipment usage, minimize electricity costs and minimize residential consumer discomfort. The DLC system schematic in Fig. 3 is divided in three sections: generation, distribution and demand.

Inputs to the distribution side are: the desired aggregated load demand from the system operator and the household load demand from the smart meter. The control of DEWH is performed from the distribution side using the BPSO controller which output the control signal to the smart meters.

The thermal model of the DEWH described in (1) is used for the determination of the water heater temperature from the data collected by the smart meters as described in Section II. The maximum temperature setpoint for each water heater and the desired aggregated load, which is provided either by the system operator or by the distribution side, is used by the BPSO for load-reshape objectives such as peak shaving, load shifting, and valley filling.

Using BPSO, water heaters are represented by agents as particles that move through the solution space by updating their velocity and position from (2) and (3). The values are then discretized as in (4) and (5). The acquired discrete particle positions are evaluated by the following fitness function:

$$F = \sum_{i=0}^{N} (|Td_i - Ta_i| \cdot w_1 + |Pd - Pa_i| \cdot w_2) \tag{6}$$

where:
$N$ : number of water heaters;
$Td_i$ : maximum water temperature setpoint;
$Ta_i$ : estimated water temperature;
$Pd$ : desired aggregated load;
$Pa_i$ : water heater load;
$w_1$ : aggregated load weight factor;
$w_2$ : temperature weight factor;

The objective of the fitness function in (6) is to minimize the aggregated peak load demand and maximize the water heater temperature during a 24 hour period. Objectives are evaluated every 15 minutes via BPSO. A trade-off exists between load demand and the temperature of the water since by reducing power to the water heater, the temperature of the water heater is decreased. The temperature weight factor, $w_1$, is greater than the aggregated load weight factor, $w_2$, in order to increase the customer satisfaction.

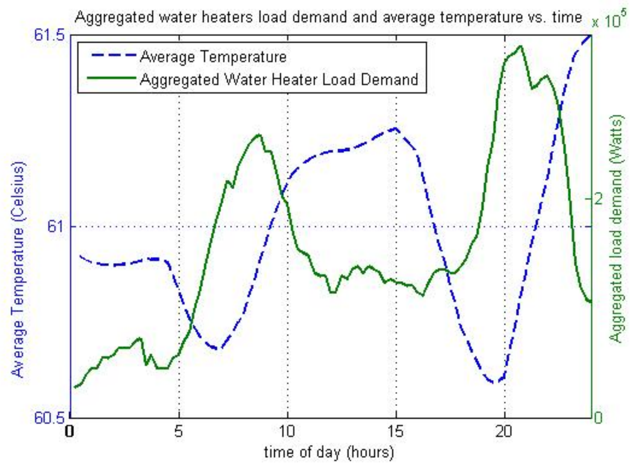


Fig. 2. Average temperature and water heater load simulation for the uncontrolled system

## IV. Results

A Matlab simulation of the new DSM program using the DEWH was performed. The system without control from the utility is simulated using smart meter household load data from 200 households. The average temperature of the hot water, and

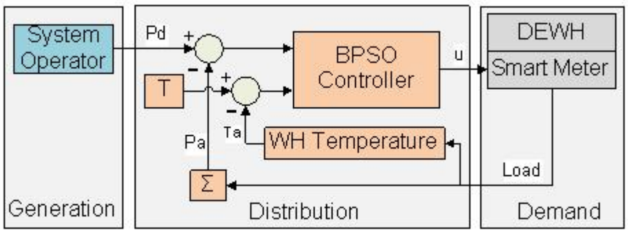


Fig. 3. Direct load control system schematic for the control of DEWH

the aggregated hot water heater load demand with no DLC are calculated and shown in Fig. 2.

The DLC system, as presented in Fig. 3, is then simulated using the parameters for the particle swarm optimization and objective shown in TABLE I. The results of the simulation are shown in Fig. 4 and demonstrate the shaving of peak loads and filling of the valleys resulting from the load control. It is noted that at the first peak of the day, the peak load value is reduced by 100kW and at the second peak of the day, the peak load value is reduced by 150kW. Given that the simulation was performed for 200 households, this represents approximately 500W-750W per household at peak load time. Given that the DEWH element is 3kW, then this means that about 1 out of 4 to 1 out 6 household water heaters are able to be controlled at peak time. These values are completely scalable and could be extrapolated to distribution feeders with many more residential loads on them. The potential cost saving for the utility and consequently the user for 200 households are \$1.260 and can be scaled to the Saint John population of 60.000 which can provide savings of \$378.000.

The parameter values found that optimize the result are $V_{max}$, $w_1$ and $w_2$, since if any of them is modified either the peak load increases or customer satisfaction is significantly compromised.

The average temperature with the BPSO control is kept within acceptable limits, and the aggregated water heater load demand is maintained fairly constant throughout the day as shown in Fig. 5.

TABLE I
SIMULATION PARAMETERS OF BPSO AND OBJECTIVE FUNCTION

| Parameter | Value |
|---|---|
| Vmax | 1.0 |
| Particles | 200 |
| Iterations | 100 |
| $w$ | 1.0 |
| $c_1$ | 2.0 |
| $c_2$ | 2.0 |
| $w_1$ | 10.0 |
| $w_2$ | 1.0 |
| Pd | $\sum_{i=0}^{24} \frac{Pa_i}{24}$ |
| $Td_i$ | $T_{max}$ |

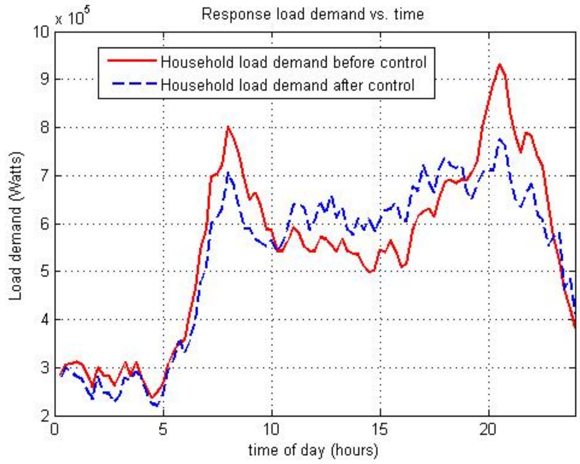


Fig. 4. Aggregated load demand response simulation using BPSO to control DEWH

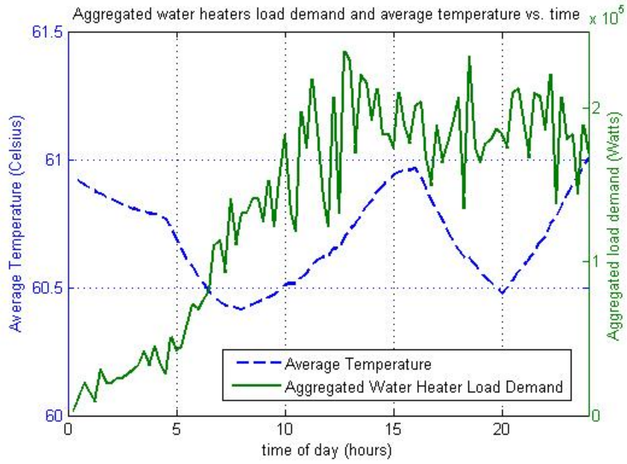


Fig. 5. Aggregated load demand response simulation using BPSO to control DEWH

## V. CONCLUSION

Discrete BPSO is shown to be an effective method for demand side management using domestic electric water heaters. The BPSO algorithm has the advantages that it is simple to implement for discrete variable problems, and gives very promising results.

The key factor is that a compromise between the load management and residential costumer satisfaction objectives is accomplished using BPSO, where such programs were not successful in the past because they have not consider the water temperature of the DEWH to keep an satisfactory comfort level of the costumer. Our approach is feasible to be implemented because of the water temperature is included in the objective function to schedule DEWH. The proposed system in this study is constrained by satisfaction by giving higher weight to the temperature objective in the BPSO optimization program on the DLC of DEWH.

Results of applying the proposed system to 200 household DEWH clearly show that it is an effective load management program for cost savings and power system stability.

## ACKNOWLEDGMENT

The authors would like to thank Mostafa Shad for the set-up of the model parameters for the domestic water heater.

## REFERENCES

[1] J. van Tonder I.E.Lane, “Load model to support demand management decisions on domestic storage water heater control strategy,” *IEEE Trans. Power Syst.*, vol. 11, no. 4, pp. 1844–1849, Nov. 1996.

[2] K.-Y. Huang and Y.-C. Huang, “Integrating direct load control with interruptible load management to provide instantaneous reserves for ancillary services,” *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1626–1634, Aug. 2004.

[3] X. Xiong and W. Li, “A new under-frequency load shedding scheme considering load frequency characteristics,” in *Proc. 2006 Int. Conf. on Power Syst. Technol.*, 2006, pp. 1–4.

[4] I. Hiskens and B. Gong, “Proc. mpc-based load shedding for voltage stability enhancement,” in *Proc. 44th IEEE Conference on Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC ’05*, Dec. 2005, pp. 4463–4468.

[5] M. H. Nehrir, B. J. LaMeres, and V. Gerez, “A customer-interactive electric water heater demand-side management strategy using fuzzy logic,” in *Proc. IEEE Power Eng. Soc. 1999 Winter Meeting*, vol. 1, Jan.-4 Feb. 1999, pp. 433–436.

[6] M. Nehrir, R. Jia, D. Pierre, and D. Hammerstrom, “Power management of aggregate electric water heater loads by voltage control,” in *Proc. IEEE Power Engineering Society General Meeting, 2007*, June 2007, pp. 1–6.

[7] P. Govender, A. Ramballee, and S. A. Moodley, “A load shedding controller for management of residential loads during peak demand periods,” in *Proc. 2004 IEEE Africon. 7th Africon Conference in Africa*, vol. 2, Sept. 2004, pp. 729–734.

[8] C. N. Kurucz, D. Brandt, and S. Sim, “A linear programming model for reducing system peak through customer load control programs,” *IEEE Trans. Power Syst.*, vol. 11, no. 4, pp. 1817–1824, Nov. 1996.

[9] B. Ramanathan and V. Vittal, “A framework for evaluation of advanced direct load control with minimum disruption,” *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1681–1688, Nov. 2008.

[10] S. Tiptipakorn and W.-J. Lee, “A residential consumer-centered load control strategy in real-time electricity pricing environment,” in *Proc. 2007 39th North American Power Symposium, NAPS*, 2007, pp. 505–510.

[11] N. Lu and S. Katipamula, “Control strategies of thermostatically controlled appliances in a competitive electricity market,” in *Proc. IEEE Power Engineering Society General Meeting, 2005*, vol. 1, June 2005, pp. 202–207.

[12] B. Rautenbach and I. E. Lane, “The multi-objective controller: a novel approach to domestic hot water load control,” *IEEE Trans. Power Syst.*, vol. 11, no. 4, pp. 1832–1837, Nov. 1996.

[13] J. Kennedy and R. C. Eberhart, “A discrete binary version of the particle swarm algorithm,” in *Proc. IEEE International Conference on Systems, Man, and Cybernetics,1997. ’Computational Cybernetics and Simulation’*, vol. 5, Oct. 1997, pp. 4104–4108.

[14] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proc. IEEE International Conference on Neural Networks, 1995*, vol. 4, Nov/Dec. 1995, pp. 1942–1948.

[15] M. Pedrasa, T. D. Spooner, and I. F. MacGill, “Scheduling of demand side resources using binary particle swarm optimization,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1173–1181, Aug. 2009.

[16] B. Mozafari, T. Amraee, and A. M. Ranjbar, “An approach for under voltage load shedding using particle swarm optimization,” in *Proc. IEEE International Symposium on Industrial Electronics, 2006*, vol. 3, July 2006, pp. 2019–2024.

[17] L. Paull, H. Li, and L. Chang, “The development of a fuzzy neural system for load forecasting,” in *Proc. Canadian Conference on Electrical and Computer Engineering, 2008. CCECE ’08*, May 2008, pp. 923–926.

[18] L. Paull, D. MacKay, H. Li, and L. Chang, “A water heater model for increased power system efficiency,” in *Proc. Canadian Conference on Electrical and Computer Engineering, 2009. CCECE ’09*, May 2009, pp. 731–734.