Predictive Energy Balance for Solar Hot Water Systems

M.K. Dennis
Centre for Sustainable Energy Systems
Australian National University
Canberra ACT 0200
AUSTRALIA
Telephone: +61 02 6125 3976
Facsimile: +61 02 6125 0506
E-mail: mike@faceng.anu.edu.au

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Abstract
Solar hot water systems necessarily require storage due to a time difference between solar supply and hot water demand. Typically the storage vessel uses an auxiliary heater to maintain a volume of hot water during periods of low insolation. The operation of this heater is controlled by a reactive device called a thermostat. This paper presents an advanced control solution to allow the thermostat to operate with discretion so that less solar energy is displaced by the operation of the auxiliary heater. The control algorithm is based on a predictive energy balance, although its behaviour may be modified by human input.

1. INTRODUCTION

Optimisation of the performance of domestic storage hot water systems has received limited attention in recent times despite the availability of a host of enabling technologies. Although there have been some approaches to this subject (Furbo 2000, Prud’homme and Gillet 2000) few practical working solutions have been found in the literature. This paper focuses on enhancing the performance of the thermostat of the hot water storage tank.

1.1 Thermostats

The thermostat is an automatic temperature switch that controls a powerful heater in a hot water storage vessel. It generally has two fixed temperature settings, one to switch the water heater ON and another to switch it OFF. The reader might identify several shortcomings of this approach:

1. The temperature settings are fixed
2. The thermostat’s position in the storage vessel is fixed
3. The thermostat switches a very powerful heater
4. The thermostat is indiscrete with regard to switching time
5. The thermostat is reactive to falling tank temperature
6. The thermostat’s action is immediate

The implications of simplistic control of the reactive and aggressive behaviour of the thermostat are that the hot water system performs poorly from an energy efficiency and a cost point of view. When used in conjunction with a solar collector, the performance is even worse. After a typical peak morning or evening load, the thermostat reacts to a drop in tank temperature and switches the heater immediately, thereby displacing the less powerful solar input from the system. A similar effect happens after the evening peak load. The solar collector then has either no work to do or will operate at a low collection efficiency due to the elevated water temperature
now present in the storage vessel. This may be viewed as an opportunity loss. Furthermore, the thermostat will continue to switch the heater on periodically in times of no demand (eg overnight) and maintain an unnecessarily large volume of water at elevated temperatures, thereby increasing storage parasitic losses. The thermostat remains because it is a simple, cheap and reliable device.

The challenge of this paper is to control the action of the thermostat to provide a degree of foresight and patience to its operation.

2. Description of the Algorithm

The working of a hot water system is governed by its main function i.e. to provide a quantity of hot water at a minimum temperature at a given time. A smart algorithm saves energy by delaying heating of the water in the storage vessel to the last possible moment. Thus, the controller must be able to predict an energy balance for the tank some time into the future. This time period is denoted the horizon of the storage vessel and is dictated by the relationship between the tank volume and the power of the heating sources.

Example: For a 300L tank and a 2.4kW heater, the heating horizon is approximately 7.3 hours

Any hot water load occurring beyond the horizon can have no effect upon the decision to switch the heater on NOW.

The energy balance for the storage vessel is one of energy supply and demand:

\[ \text{Electric/Gas Heating} + \text{Solar Assistance} = \text{Load Drawn} + \text{System Losses} \]

Once the last three components have been quantified from the current time to the vessel’s horizon, any difference can be made up using supplementary energy from the electric/gas heater. The controller understands that this heating does not occur immediately and that a load effectively casts a shadow of influence back in time.

2.1 Defining the State Variable

The control algorithm aims to control the quantity of energy stored in the form of hot water in the tank. An indication of the state of the tank is defined as

\[ K = \frac{(E_{\text{avail}} - E_{\text{load}})}{E_{\text{load}}} \]

![Fig 1. Thermostat Control Performance Indicator](image)
Perfect performance is indicated by $K=0$ and only positive values of $K$ are acceptable, indicating that there is sufficient energy stored in the tank to meet the upcoming load. Positive values of $K$ indicate excessive energy storage. One may readily see that $K$ is a useful feedback variable that the controller may use to learn and modify future behaviour.

2.2 Energy Supply

Although heat input from gas or electric heaters are readily quantifiable, solar input is more difficult. The solar system may be modelled or learnt so that the controller is aware of a relationship between insolation, collector inlet temperature, collector flowrate and energy recovered. If an insolation profile is available, then the solar energy input may be quantified on a predictive basis. Local insolation forecasts of suitable temporal resolution are available and work continues with the Bureau of Meterology to provide this service.

If weather information is not communicated to the controller in a timely fashion, the controller assumes no solar input for the purposes of the energy balance and thus operates in a conservative manner. There will have some indication of past performance from the tank state feedback variable. This provides no indication for future energy balances.

Readers will note the need for communication of this information to the controller. These algorithms are designed to run in a distributed intelligence environment whereby nodes are connected to a central intelligent server via a network. This is happening in many cities around the world and indeed the controller used for validation of these algorithms is network enabled also.

2.3 Energy Demand

It is important that the controller be able to forecast how much energy will be drained from the system and at what time so it is able to call upon the correct amount of heating to satisfy this demand without storing excess heat for extended periods and thereby incurring opportunity and parasitic losses as previously discussed.

It would seem unwise to try to provide the controller with a pre-defined load profile since every hot water installation will be different in some way. It would be better if the controller was able to learn to forecast this load on a case by case basis. Fortunately, Artificial Neural Networks (ANN) offer a solution.

A full explanation of the ANN is outside of the scope of this paper. In summary, an input data set consisting of the time of day, day of week and the current tank state variable is supplied to the ANN and this in turn uses its internal mapping to provide a forecast of the expected energy load over the tank horizon time. Throughout operation of the tank, the tank state variable essentially indicates the error in the energy balance prediction and this is used as a feedback variable to assist learning in the ANN. Noteworthy is that the structure of the ANN is based on Adaptive Resonance Theory (ART) (Grossberg, 1988) so that new learning information does not require new training regimes for the ANN.

The hot water load is specified in energy rather than volume terms and reflects to the difference between the water supply temperature and a hot reference temperature usually taken to be the thermostat OFF temperature. Furthermore, the ANN recognises tank losses and water draw as equivalent in predicting load from the system.

2.4 Boost Shadow Algorithm

Now that the components for the predictive energy balance are available, a time profile for the net energy required from the heater may be determined. Each load within the time horizon has the ability to affect the decision of the controller whether to switch on the heater NOW since each load effectively casts a time shadow back towards the current time. The length of the shadow is representative of the power of the heater. Figure two shows how a low powered heater must be switched on earlier than a high powered heater to meet an upcoming load. Multiple loads within the horizon simply accumulate the area of the shadow as indicated in Figure 3. In this example, notice how Load1 would not require heating to be switched on NOW if it wasn't for the cumulative shadow cast be Load2 (provided Load 2 also occurs within the tank horizon).
The algorithm thus works backwards from the tank horizon, accumulating heating shadow from loads and decaying them at the rate of the heater power. If the balance is greater than zero at the current time, the heater must be switched ON.

3. Modeling the Predictive Control

The TRNSYS modelling package (Klein 1996) was used to analyse the performance of a typical hot water system with and without the predictive controller. The system simulated a solar hot water system located in Canberra serving a family of four in a domestic dwelling.

The simulation used typical meteorological year weather data (Morrison et al 1988) and assumed perfect availability of insolation forecasts. It also assumed perfect knowledge of upcoming load events and did not model the artificial neural network. This load was derived from a stochastic probability distribution and has the same total energy as Australian Standard AS4234 although different spectral content. The simulation thus provides a ceiling for performance for real controllers. Nonetheless it is a useful exercise to get an idea of the potential for this technology.

Figure 4. graphically demonstrates the algorithm in action. The flat purple line indicates tank temperature, the rounded blue line indicates insolation while the light blue spikes indicate load being drawn from the system. Finally, the red line indicates the switching of the heater.

One notices immediately that a thermostat provides too much heat, and unnecessary overnight heating is apparent. Also visible is the rapidity of reheating of the water after a load event and the small solar contribution evident. The predictive algorithm allows the tank temperature to drop between loads knowing that it is able to
meet any demand just-in-time. The model confirms that the ideas presented do work and provides an indication of potential energy and cost savings over a conventional thermostat based solar storage tank.

3.1 Simulation Results

The results presented indicate annual performance for a commercial 300L storage vessel connected to 3.8m² of solar collector in Canberra, Australia. A total of 3900kWh of hot water is drawn from the system annually. The reader should understand that these results are indicative of the control algorithm performance and that the results are sensitive to system configuration and how the system is used. The load profile is biased towards high loads in the early morning and evening after sunset. This load profile differs substantially from the Australian Standard profile and is more realistic in the author’s view. Some physical modifications would be required in the storage tank to realise these benefits, including a variable effective heater location. These modifications will be discussed in a future paper.

<table>
<thead>
<tr>
<th></th>
<th>Thermostat Control</th>
<th>Predictive Control</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Auxiliary Energy Cost</strong> ($)</td>
<td>526</td>
<td>365</td>
<td>- 31 %</td>
</tr>
<tr>
<td><strong>Solar Fraction</strong> (%)</td>
<td>19.6</td>
<td>37.0</td>
<td>+ 89 %</td>
</tr>
<tr>
<td><strong>Store Efficiency</strong> (%)</td>
<td>69.9</td>
<td>82.0</td>
<td>+ 17 %</td>
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Table 1. A Performance Ceiling for the Predictive Control Algorithm

DISCUSSION

This “just-in-time” approach implies that the minimum volume of hot water to meet an upcoming load should be maintained at all times. Since the storage tank is not always full of hot water, some thermal stratification will result and this means that the solar collectors will run more efficiently from lower temperature feed water near the bottom of the tank. Indeed, any effects that enhance thermal stratification within the storage vessel will assist in improving efficiency.

The just-in-time approach also implies a greater risk of running out of hot water and with this in mind, the algorithm must have the ability to assess when aggressive or conservative behaviour is appropriate. This behaviour is modulated by the accuracy to which the energy balance may be predicted. One might argue that the ultimate just-in-time system is an instantaneous heater. This is true for all but solar systems that necessarily require storage to buffer the time offset between supply and demand, and where complex energy tariff structures exist.

Each component in the energy balance is accompanied by an uncertainty quantity and this determines how aggressive the algorithm becomes in minimising additional hot water. This “conservative energy” could manifest in two ways

- Additional energy storage as additional volume at the thermostat temperature
- Additional energy storage as additional temperature in the minimised volume.

Models suggest that these schemes provide very similar energy efficiency penalties for the additional energy storage. However the increased temperature scenario seems to result in less destratification loss.

This conservatism implies that the user of the system has some influence on the behaviour of the controller. Indeed the user may wish to override the controller (switching the heater either ON or OFF) and the load learning algorithm will inadvertently pick up the change in tank state variable as an indication of a large error in
its prediction.

Many hot water services are fitted with tempering valves to ensure that scalding water cannot be delivered to a hot water service. Health standards demand that the storage vessel maintain a minimum temperature setting to prevent bacterial growth, typically 55°C to 60°C. The temperature setting for the tempering valve is typically lower than the thermostat settings and so any water in the store above this temperature is considered useful in that it’s volume may contribute to the hot water load. Thus, a degree of de-stratification in the tank between loads may not always be detrimental.

3 CONCLUSION

A predictive energy balance algorithm is presented that endows hot water system thermostats with virtues of patience and foresight. The more accurately the energy balance may be determined, the more aggressive the controller may become at maximising savings while maintaining reasonable reliability.

The effectiveness of the predictive algorithm is sensitive to the suitability of the initial hot water system design and its suitability for the load drawn from it. With simulated stochastic loads, modelling suggests energy and cost savings in the order of 30% are available, although not necessarily achievable. A controller has been constructed and the various components of the infrastructure are being assembled to validate the algorithm and to assess what savings can actually be realised.

This approach will work on gas or electrically heated tanks, but provides greatest benefit in solar assisted domestic water heating systems.

4 ACKNOWLEDGEMENTS

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5 REFERENCES


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