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Control-oriented modelling of stratified storage tanks: an enhanced approach

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Abstract: *Energy storage devices, such as stratified tanks, play a decisive role in managing the mismatch between renewable energy sources and loads. As part of a larger study on advanced predictive control for a solar district heating system (the Drake Landing Solar Community, DLSC), this paper investigates a control-oriented modeling method of a short-term energy storage device consisting of two stratified tanks connected in series. In a conventional modeling approach for stratified tanks, incoming flows are delivered to one of several thermal "layers" in the tank as a function of their temperature. This concept is expanded by allocating different fractions of the received flowrate to the different layers in the tanks. DLSC data is used to calibrate the model; the accuracy of this model is then compared with the more traditional approach. Finally, the benefits of using such a model for control purposes are discussed.*

Keywords: *predictive control, control-oriented model, thermal energy storage, stratified storage, district heating*

INTRODUCTION

The Drake Landing Solar Community (DLSC), located in Okotoks (Alberta, Canada), has an innovative district heating system, mostly supplied by solar energy, that provides the space heating demand of 52 single-detached homes (Sibbitt et al., 2012). Different novel technologies have been integrated into this community, including solar thermal collectors for energy harvesting and borehole thermal energy storage (BTES) for long-term storage of solar energy (Figure 1).

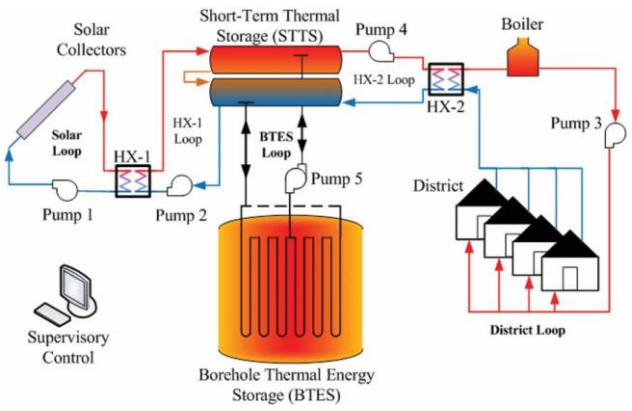

Figure 1: Schematic of the DLSC district heating system (Quintana and Kummert, 2015)

One of the key elements in the operation of the system is the short-term thermal storage (STTS) that makes the link between the solar loop, the BTES and the houses. The main control sequences are based on the interaction of the STTS with the remaining components of the district heating. In operation since 2007, the DLSC is performing beyond design expectations: it achieved a solar fraction of 100% in 2015-16, which means that all the space heating demand was supplied by solar energy, without requiring the use of the backup gas boiler.

Despite this outstanding performance, there is room for improvement. For instance, several operational upgrades may be deployed to maintain such a high solar fraction in the future. In particular, predictive control based on weather forecast may be implemented to enhance the operation of the STTS. To achieve this goal, control-oriented models are a valuable tool. Since they enable a rapid assessment of the interaction of the system components, such models thus assist in making better decisions.

In this context, modelling the STTS is essential. The STTS consists of two 120-m^3 horizontal tanks connected in series (Figure 2). Baffles are installed halfway up the tank to increase the thermal stratification. The temperature distribution inside the tank is monitored with six temperature sensors (*TS*) that are representative of the top, middle and bottom of each tank. Water is directly circulated towards the different (solar, district and BTES, as shown in Figure 1) loops. The flow direction towards the BTES loop depends on the operation mode (heat injection/extraction).

Due to the central role of the STTS in the district heating system, modelling and controlling it properly is essential. However, developing an appropriate control-oriented model is no easy task: the model should be simple enough to be quick and practical, yet accurate enough to consider the system complexity. Existing models can either be too detailed and require high computational time, or be too simple and not necessarily very accurate.

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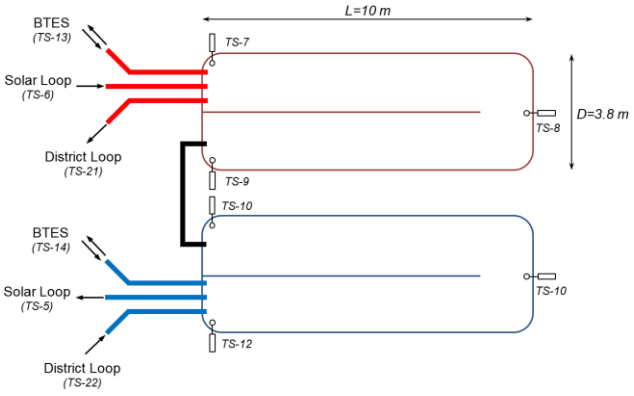

Figure 2: Short-term thermal storage (two water tanks) used in the Drake Landing Solar Community

The objective of this paper is to develop a simplified control-oriented model for stratified storage tanks that performs better than existing models. Firstly, an overview of existing modelling approaches is carried out. The proposed control-oriented model is then developed. A procedure to "update" periodically the state of the model is introduced as well. Finally, accuracy, benefits and applications for using the proposed model and the update procedures are discussed.

LITERATURE REVIEW: OVERVIEW OF MODELING STRATEGIES

In this section, heat transfer mechanisms occurring in storage tanks are described. Afterwards, various storage models are investigated, from more detailed to simple approaches. Limitations of existing models for control purposes are finally addressed.

Heat transfer mechanisms

Water storage tanks act as buffer systems. As shown in Figure 2, water is supplied to specific loops and returns, either hotter (e.g., solar loop) or colder (e.g., district loop) to the tank. Physical entry ports are in general located at bottom and top of the tank, corresponding to colder and hotter water, respectively. This arrangement results in a complex circulation of water inside the tank, mainly caused by fluid streams and density differences arising from temperature differences. There is also a certain degree of thermal stratification, i.e., a distribution of water at different temperatures, from the hottest at the top to coldest at the bottom (Duffie and Beckman, 2006). However, several destratification factors affect this temperature distribution; for example: fluid mixing during charge and discharge cycles, heat losses through the tank envelope to the environment, heat conduction from hot to cold water layers, and conduction within the tank walls that induces convective currents (Kleinbach et al., 1993).

From an operational perspective, preserving stratification can be of significant interest when both high and low temperatures are simultaneously desired (Han et al., 2009). For instance, using cold water improves solar collector efficiency while high water temperature makes it easier to satisfy heating loads. Additional measures can be used to enhance stratification, such as entrance port configurations (Shah and Furbo, 2003) and baffles (Altuntop et al., 2005). Concepts of storage stratification efficiency (Haller et al., 2009) and state of charge (Leeuwen et al., 2017) are thus essential for the characterization of a stratified tank.

Storage models

Depending on the application, several storage tank configurations can be selected; among others, horizontal and vertical tanks, single and multiple inlet and outlet ports, auxiliary elements, internal and external heat exchangers, tanks with or without baffles, etc. (Han et al., 2009). Diverse modelling methodologies are used as well. While 2-D and 3-D methods based on mass, energy and momentum balance equations are used to investigate complex phenomena within the tank (Han et al., 2009), simple 1-D methods (particularly nodal methods) are suitable for control purposes. In such approaches, the tank is divided into a fixed number of water layers (or nodes) at different temperatures (Kleinbach et al., 1993) that are representative of stratification. Internal water flows induced by density and other factors (conduction in water and between water and tank wall, convection, etc.) can be assumed. This modelling methodology will be explained in-depth in the next section. An alternative consists in using gray-box model and identification procedures (De Ridder and Coomans, 2014) where appropriate parameter matrices must be developed and calibrated with data. The selection of node number then mainly depends on application and tank size. Fully mixed (i.e., 1-node) tank models can be accurate enough for many applications (Badescu, 2008; Halvgaard et al., 2012), although a relatively high number of nodes may be needed (Kleinbach et al., 1993; Candanedo and Dehkordi, 2014). There also exist plug-flow models where the tank is approximated to a number of variable segments whose size varies with entering and leaving flow rates and node temperatures (Kleinbach et al., 1993). In such methods, the resolution of traditional differential equations is not necessarily performed (Duffie and Beckman, 2006). Note that most of these approaches have been implemented in TRNSYS and consider various levels of details (Allard et al., 2011). Additional information about storage modeling is given in (Han et al., 2009).

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Limitations of existing models for control purposes

Control-oriented models are intended to be simple enough to provide quick calculations (while being reasonably accurate), and to facilitate their calibration with measured data. For this purpose, being able to associate variables in the model with their corresponding measured data is essential. This possibility makes nodal methods attractive, since the values measured by the sensors can be associated with the values predicted by the model. Moreover, most of the aforementioned studies have been performed on smaller-scale storage tanks, e.g., from 200 L (Leeuwen et al., 2017) up to 20 m^3 (Candanedo and Dehkordi, 2014), where the degree of stratification is not as significant as for the larger-scale system used in Drake Landing (240 m^3). In such a situation, a more detailed model (i.e., higher number of nodes) may be required. In this case, however, the calibration of gray-box models based on parameter matrices as proposed by De Ridder and Coomans (2014) could be too cumbersome. On the other hand, density-based models (Kleinbach et al., 1993) could be less accurate and may need some improvements (e.g., calibration of additional parameters).

METHODOLOGY: DEVELOPMENT OF CONTROL-ORIENTED MODEL

This section discusses the methodology used to develop a control-oriented model for the stratified storage tank used in DLSC. This approach is based on a modification of the nodal density model proposed by Kleinbach et al. (1993).

Kleinbach's simplified model based on density distribution

The multi-node model proposed by Kleinbach et al. (1993) relies on a basic principle: regardless of the position of the physical inlet ports, *water entering the tank goes towards the node (or water layer) that better matches its density*. In practice, this means that the flow goes to the node that has the closest temperature to that of the incoming fluid. This "virtual positioning" of the entry point enables an accurate representation of stratification. The physical locations of the outlet ports (e.g., typically near the bottom for sources or near the top for loads) are usually considered in the model formulation. The rest of the water flows between nodes are distributed inside the tank in order to respect conservation of mass.

The basic assumptions of this model, summarized in Figure 3, include:

- The thermal properties of water are constant.
- The temperature within each node is uniform, and constant within a time step.
- Entering and leaving water flows are unidirectional.
- The water flow enters and leaves the tank at such low speeds that additional mixing is avoided.
- The water flow entering the tank goes "perfectly" to the corresponding node by density, without losing energy to the other nodes.
- Fluid streams are fully mixed before flowing into the next node.
- Conduction between water layers and between water and tank wall is neglected.

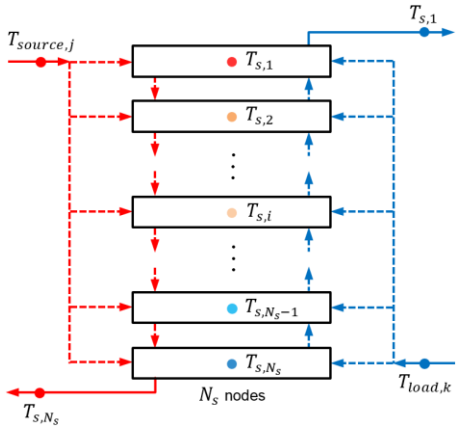

Figure 3: Schematic of the simplified model based on density distribution for stratified storage

Example of the application of the Kleinbach's traditional method

As an example, consider a 4-node tank characterized by temperatures of 50, 45, 40 and 35°C, illustrated in Figure 4. The physical inlet port is located in the first node, at the top of the tank. If water from a source comes in at 42°C, it is assumed that it will go by density to the third node. In other words, the "virtual port" is located at the 3rd node. To ensure that conservation of mass is respected, mass fraction coefficients (in this case, 0 or 1) are used. These coefficients represent the flow received by each node directly from the source (F_{source}), the flow entering each node from the node above ($F_{s,in}$), and the flow leaving each node ($F_{s,out}$).

Heat losses to the surrounding air have also been taken into account by assuming an overall heat loss coefficient of 0.05 kW/K for each tank node, and a storage environment temperature of 15°C. After a time step of one hour, the temperature of the first two nodes remains almost unchanged (i.e., heat losses only), whereas the temperature

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of the nodes 3 and 4 changes noticeably (i.e., it increases) due to the received flow.

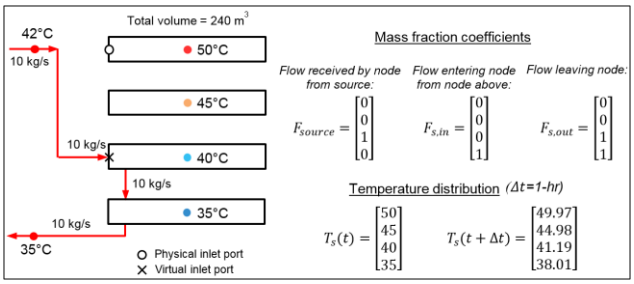

Figure 4: Illustration of mass and energy balances applied to a 4-node tank (traditional approach)

Note that a similar approach is used for the water coming from the loads. The only difference is that the physical inlet and outlet ports will be at the bottom and the top of the tank, respectively. Further details on the mathematical formulation is given in (Duffie and Beckman, 2006).

Proposed modification: Advanced Flowrate Distribution (AFD)

In Kleinbach's formulation (Figure 4), only the nodes located at the "virtual inlet port" or below it are affected by the flow received from the source. Therefore, the actual position of the physical inlet port is practically irrelevant for modelling purposes.

However, it is reasonable to assume that the trajectory followed by the water from its physical inlet port to its corresponding node (i.e., the location of the "virtual inlet port") has an impact on the upper nodes of the tank. The thermal energy of the water flow will be partially "lost" in the path before reaching the "virtual inlet port" node. These heat losses depend on the path followed by the water, as well as on the difference between flow and node temperatures.

In order to account for these heat transfer losses, this paper proposes an *advanced flowrate distribution* (AFD) method. The AFD approach consists in:

(a) introducing a new parameter: the minimal flow rate allocation coefficient α_{min},

(b) calculating percentages of flow allocation for intermediate nodes,

(c) modifying the mass fraction coefficients accordingly.

The parameter α_{min} is the fraction of the flow that reaches the lowest "virtual inlet port", i.e., the coldest node at the bottom. In Kleinbach's original formulation, α_{min} is 100% (i.e., all the fluid thermal energy is received by the virtual inlet port even if the fluid has to go the bottom of the tank).

If the virtual node is not at the bottom node, a simple linear regression going from 100% to α_{min} is used to establish the flow percentage corresponding to the "virtual node". The loss factor between two successive nodes is determined as follows:

$$LF = \frac{100\% - \alpha_{min}}{N_s - 1} \quad (1)$$

where N_s is the node number. To respect the conservation of mass, this quantity that does not reach the "virtual node" is then necessarily absorbed in the previous nodes.

Figure 5 illustrates the proposed methodology for the case of a 4-node tank. In this example, the minimal flow rate allocation coefficient (α_{min}) is 40%. This means that if the temperature of the incoming fluid determines that the virtual port should be at node 4, this node would receive 40% of the fluid.

It is further assumed that, with respect to mass balance equations, a constant portion of 20% of the flow is "lost" to the nodes 1, 2 and 3 (as shown in the last row of the matrix). In fact, due to the constant volume associated to each node, the distance covered by the water flow may be identical for each node. Moreover, heat losses depend on the temperature difference between the received flow and the tank nodes, and the time that water takes to pass through the node is proportional to the density difference. For simplicity purposes, it is assumed that these effects are cancelled out.

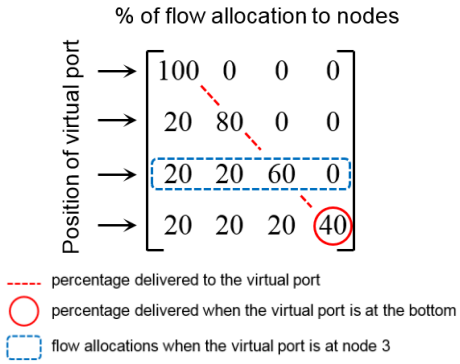

Figure 5: Example of flow allocation in 4-node tank for α_{min} = 40%

To account for the cases when the virtual port is *not* at the lowest node, a linear regression between 100% and α_{min} (40% in this case) is used to determine the flow rate allocation corresponding to the virtual port. In the case of Figure 5, these percentages are shown in the main diagonal for the different positions of the virtual inlet port. For example, if the virtual port were at node 3, this node would

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receive 60%, while nodes 1 and 2 would receive 20% of the flow (Figure 5).

In the AFD method, α_{min} may also take *zero or negative* values. This means that the thermal energy of the entering fluid does not reach the node that should correspond to its density. As α_{min} decreases, it implies that more heat is "lost" in the upper layers. For example, if α_{min} is equal to -20% and if the virtual port were at node 3, this node would receive 20%, while nodes 1 and 2 would receive 40% of the flow (Figure 6).

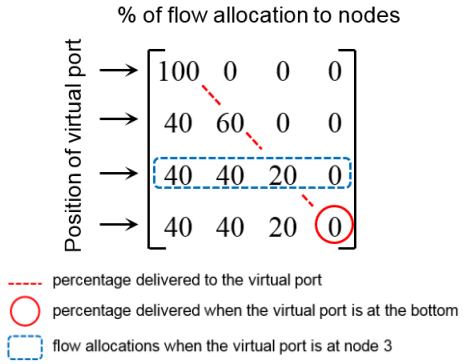

Figure 6: Example of flow allocation in 4-node tank for α_{min} = -20%

Example of the application of the AFD method

Consider the 4-node tank used in the previous example. As previously mentioned, the virtual port corresponding to the incoming water at 42 °C is at node 3. This time, the AFD method is applied (Figure 7) and it is assumed that the system behaves according to the model in Figure 4. This means that node 3 receives only 60% of the flow, while nodes 1 and 2 receive 20%. Unlike the previous example in which only the bottom two nodes were affected, the incoming flow has an effect on the temperature of all nodes.

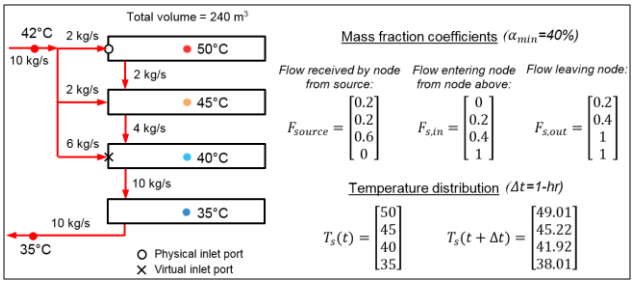

Figure 7: Illustration of mass and energy balances applied to a 4-node tank (proposed AFD method)

"State update" procedure

In addition to the proposed AFD method, another technique that may be used to improve model accuracy for control purposes is the "state update", described below.

In a design-oriented model, a simulation takes place over a long period (e.g., a year) and there is no periodic comparison with real conditions. In contrast, in the case of control-oriented models (where the short-term system behavior is required for decision-making), it is possible and appropriate to compare the predicted states with measured temperature distribution. This exercise can be carried out at periodic intervals (e.g., 6-hr). As shown in Figure 8, deviations from data are then reset to zero every two time steps. Both the proposed AFD method, as well as the traditional approach, calculate the temperature distribution inside the storage tank after each time step, and can therefore be used to define the current state of the system.

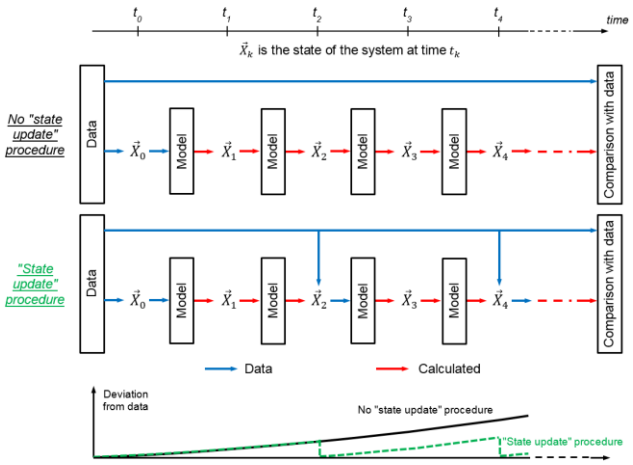

Figure 8: Description of the "state update" procedure

This "state update" requires the identification of the model variables to measured data. In the case of the short-term thermal storage used in Drake Landing, six sensors (labeled TS-7 through TS-12 in Figure 2) are monitored to assess the temperature distribution. Since there are six sensors, using a six-node model would be ideal for "state update". However, six nodes may be insufficient from an accuracy standpoint, and it may be necessary to increase the number of nodes.

For a larger number of nodes, it is then necessary to select appropriately the nodes that correspond to the existing sensors so that the measurements can be used to update the state of the model. In other words, sensor locations should be associated to specific nodes (e.g., the first sensor to the first node, the second sensor to the "middle" node of the hot tank, etc.). The rest of the nodes will be updated through

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interpolation. Due to the constant volume of each node, only specific node numbers allow the model variables to be properly identified to the measurements. For the specific case of Drake Landing with two large tanks (Figure 2), different number of nodes were considered, ranging from 6 to 38. To illustrate this "state update" procedure, the identification method gives for 6, 10 and 38 nodes:

- 6 nodes (3 per tank), with all nodes identified to sensors,
- 10 nodes (5 per tank), with nodes 1, 3, 5, 6, 8 and 10 identified to sensors,
- 38 nodes (19 per tank), with nodes 1, 10, 19, 20, 29 and 38 identified to sensors.

RESULTS: MODEL CALIBRATION AND ACCURACY

Applied to the short-term thermal storage used in DLSC, the proposed AFD model was calibrated and validated for 2015, from January 1st to December 31st. The configuration of two horizontal tanks (120 m^3) in series was considered as a single 240-m^3 tank. Interactions between water layers above and below the baffles (see Fig. 1) were neglected. Impacts of the minimal fluid allocation coefficient, model accuracy and optimal node number are discussed in this section. Computational speed is a significant factor from an operational perspective: it is worth mentioning that, using a 22-node model, it takes about 5 seconds to complete a simulation for a one-year period at 10-min time steps.

Parametric analysis of the minimal fluid allocation coefficient

In the traditional approach, the overall heat loss coefficients *UA* can be calibrated to increase the model accuracy. The AFD approach requires the calibration of an additional parameter α_{min}. As mentioned in the previous section, α_{min} cannot exceed 100%, although it may take negative values (which means that received flow loses all its thermal energy before reaching the lower node).

To assess the model accuracy, the root mean square deviation *RMSD* has been calculated based on all six measured temperatures, as follows:

$$RMSD = \sqrt{\frac{1}{N_s}\frac{1}{n}\sum_{i=1}^{N_s}\sum_{m=1}^{n}\left(T_{i,m}^{calc} - T_{i,m}^{meas}\right)^2} \qquad (2)$$

where $T_{i,m}^{meas}$ and $T_{i,m}^{calc}$ are measured and calculated temperatures, respectively, estimated for all N_s (six) sensors and the appropriately identified nodes along the year at 10-min intervals, which correspond to a total of n values per node (6 x 24 x 365 = 518,400).

The influence of α_{min} on the *RMSD* was evaluated for models using different numbers of nodes. Figure 9 shows the results. It is interesting to note that all the results obtained with the proposed AFD model are more accurate than those estimated by using the traditional approach (shown in Figure 9 at α_{min} = 100%).

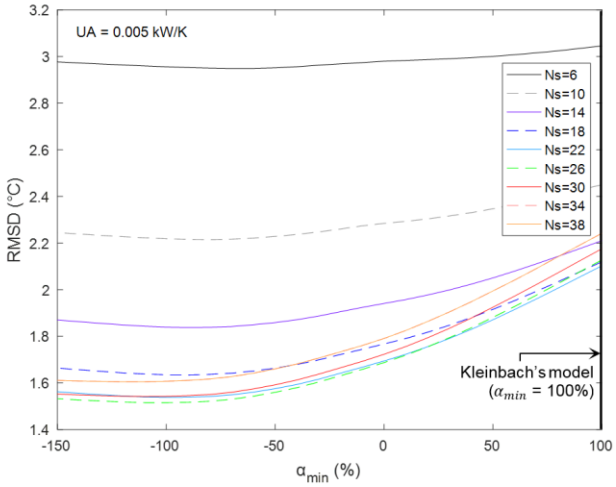

Figure 9: Effect of α_{min} on the model accuracy

From this figure, it appears that an optimal value of α_{min} exists, which seems to vary with the number of nodes, from -70% for a 6-node model down to -130% for a 38-node tank. Furthermore, it was found that using more nodes does not necessarily increase the model accuracy: an optimal number of nodes can then be estimated from optimization procedures. The negative optimal values may indicate that the received flow from the source cannot reach the tank bottom without losing all its thermal energy. Such a result is consistent with the large size of equipment used in Drake Landing (i.e., total volume of 240 m^3). Note that the optimization procedure might yield positive values of α_{min}, for instance, in the case of smaller tanks.

Calibration of model parameters

As mentioned above, the *RMSD* can be minimized by optimizing the following variables:

- the minimal fluid allocation coefficient α_{min},
- the overall heat loss coefficient *UA* for each node,
- the number of nodes N_s.

For analysis purposes, the optimization was performed for each of the number of nodes under study, i.e., 6, 10, 14, 18, 22, 26, 30, 34 and 38, and results, given in Table 1, have been compared for 6-, 22- and 26-node configurations, with and without state update procedures. Note that the optimization routines have been performed without

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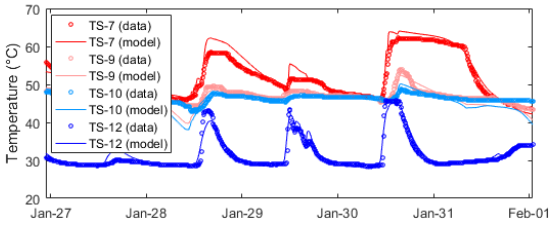
considering state update procedure. Furthermore, to illustrate the model accuracy, the STTS temperature distribution of the 22-node configuration is shown for typical periods (winter, summer); with no update in Figure 10 and with 6-hr update in Figure 11. Note that only four temperatures (top and bottom of each tank) have been given to help the visualisation of the results.

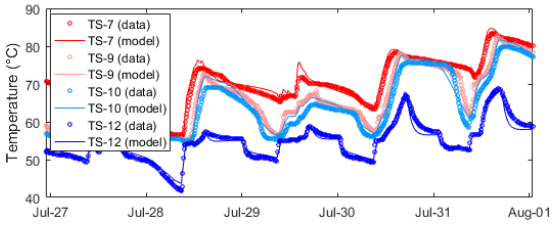
Table 1: Model accuracy for 6-, 22- and 26- node storage tanks, with and without state update procedures

RMSD	Reference model		AFD model	
	No update	6-hr update	No update	6-hr update
6-node	3.04°C	1.70°C	2.95°C	1.65°C
22-node	2.10°C	1.52°C	1.54°C	1.40°C
26-node	2.13°C	1.54°C	1.51°C	1.41°C

From Table 1, it is clear that using the proposed AFD model improves accuracy, in particular for a high number of nodes, by reducing the *RMSD* up to 29% (i.e., from 2.13°C down to 1.51°C for 26-node) for the case without state update procedure.

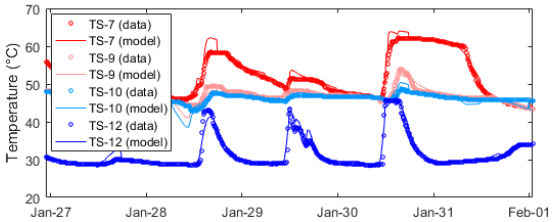


(a)



(b)

Figure 10: Temperature distribution for the 22-node configuration with no state update; (a) in winter, and (b) in summer



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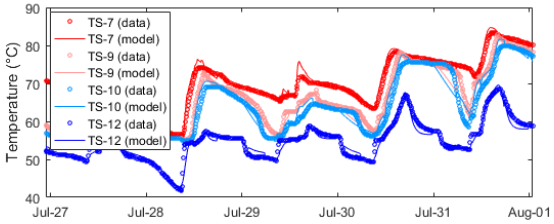

(b)

Figure 11: Temperature distribution for the 22-node configuration with 6-hr state update; (a) in winter, and (b) in summer

When state update procedures are implemented (e.g., 6-hr update), model deviation from data will be, by definition, lower (Fig. 6), but a further decrease of up to 9% (i.e., from 1.54°C down to 1.40°C for 22-node) can still be achieved. By combining both methods, the *RMSD* decreases by 33% for the 22- and 26-node configurations, and even up to 46% for the 6-node tank.

Moreover, as shown in Figures 10-11, temperature fluctuations are well represented. By comparing these figures, it appears that deviations observed with no update are also partially reduced by using the 6-hr update procedure (e.g., at the end of Jan-28 for the upper node). Thus, it allows measured temperatures to be closely follow by periodically resetting deviation to zero.

Optimal number of nodes

As shown in Table 1 and to a lesser extend in Fig. 7, the optimal number of node appears sensitive and it depends on calibration parameters as well as the model used and the state update procedure. In fact, the 22-node configuration is optimal based on the conventional Kleinbach's model while the 26-node tank yields better accuracy with the AFD model. In the latter case, however, the 22-node model seems to be more accurate when 6-hr update procedure is implemented. In such a situation, the performance of both models is quite similar (difference of 0.03°C) and using less nodes would be the preferred option considering computational time requirements. As mentioned in the literature review section, this optimal node number is quite high but it can be justified by the large size of tanks where

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a 30°C thermal stratification can be achieved (Jan-31 in Figures 10-11).

DISCUSSION: APPLICATION OF PROPOSED AFD MODEL AND STATE UPDATE PROCEDURES

The benefits of using the proposed approach, i.e., AFD model and the state update procedure, and potential model improvements are discussed in this section.

Proposed AFD model

The proposed AFD model is simple and could be of great interest when computational time must be reduced as much as possible; this is often the case for design optimization problems and control applications. Since the model needs to be calibrated, reference data is required. This data could consist of either real measurements or simulation results obtained from a more detailed model. Compared with the traditional approach, the proposed model only requires one additional parameter to calibrate: the minimal flow rate allocation coefficient α_{min}. As given in Table 1, the use of the proposed AFD model can significantly decrease the RMSD. Naturally, this reduction will certainly depend on the studied situation (e.g., volume of storage, flow rate(s) in loop(s) connected to the tank, operating temperatures, etc.).

State update procedure

The implementation of the state update procedure provides an additional gain in model accuracy for both the Kleinbach's model and the AFD models. It is worth mentioning that the implementation of the state update procedure, by itself, can also significantly increase the model accuracy. However, such improvement is limited to applications where actual temperatures are available; in particular, control procedures.

Potential model improvements

The proposed AFD model is a first step towards a simplified and accurate modelling method for stratified storage tanks. There is room for improvement depending on the application and the need for higher accuracy. For example, in this study, a linear regression based on α_{min} was used to estimate the fraction of the received flowrate that goes to the node by density. Other "laws" could then be investigated, e.g. exponential correlations, which are typical of attenuation phenomena.

Moreover, in the AFD method the fractions allocated to the nodes in the flow path depend on the value of α_{min}. In this study, they were assumed constant for each node. This approach implicitly considers the trajectory followed by the water flow; modifications could be introduced to account for the effect of fluid velocity. Other improvements might include considering heat transfer between water layers, heat transfer between the water and the tank and other flow-related effects. Finally, the impact of time step duration on the model accuracy could also be analyzed.

CONCLUSIONS

As part of a larger study on the Drake Landing Solar Community, a novel control-oriented model for stratified storage tanks has been presented in this paper. It is based on an advanced flowrate distribution of the received flow. For this purpose, a minimal flow allocation coefficient has been introduced; such modification enables to significantly increase the accuracy of the model. Furthermore, another technique that can be of interest for control purposes is presented: the state update procedure, which consists in resetting the state of the system based on measurements and thus correcting model deviations from data. Potential applications for proposed methods (i.e., AFD model, state update procedure) and suggestions for model improvements are finally discussed.

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