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Optimal Thermal Energy Storage Heatsinks for Communication Devices

[1]Jeevan Kanesan, [1]Harikrishnan Ramiah and [2]Irfan Anjum Magami

[1]Dept of Electrical Engineering, Faculty of Engineering, University Malaya, Malaysia
[2]Dept of Mechanical Engineering, Faculty of Engineering, University Malaya, Malaysia

Abstract: A thermal response model for designing optimal thermal energy storage (TES) heatsink utilized for transient electronic cooling is developed by combining Artificial Neural Network (ANN) with Genetic Algorithms (GA). The thermal response model is developed to produce the desired TES heatsink configuration such as fin thickness, fin height and number of fins that yields optimal quality factors namely longest stabilization time and lowest maximum operating temperature to average transition temperature difference. Numerical simulations carried out showed good agreement with TES experimental data available in literature. The data from numerical simulation is then used to train ANN and later the trained ANN is embedded in GA to produce the optimal TES configurations.

Key words: Thermal energy storage, Artificial Neural Network (ANN), Genetic Algorithms(GA)

INTRODUCTION

Thermal energy storage systems have been developed to manage thermal control in variable power devices such as communication systems in hostile environment namely military and fireman walkie talkie. Currently it is also gaining popularity in conventional use such as camera and mobile phones. They are capable to store energy during peak power operation and release it during periods of reduced power operation. Phase change materials (PCM) used in TES heatsinks undergoes phase transformation at the transition temperature, T_{t}, which provides load leveling capability via latent heat effect. Leoni and Amon, (1997) used paraffin as the PCM to control the operating temperature of wearable electronics and Bauer and Wirtz, (2000) had described a TES composite that incorporates pentaglycerine as the PCM. The performance of a TES heatsink is measured by its quality factors. The quality factors of TES systems are volumetric storage capacity and the thermal resistance. A good TES system requires extended period in time for heat storage as well as low thermal resistance. The extended period is also known as stabilization time. There will be a finite thermal resistance between the heat source and the PCM storage volume. Another thermal resistance connects the storage volume to the system heat exchanger. As a consequence, at the transient temperature of the PCM mass will lag behind the temperature of the heat source. This effect is characterized as maximum operating temperature to transition temperature difference. The thermal resistance is measured by using the maximum operating temperature to transition temperature difference. The major drawback of PCMs is its low thermal conductivity that poses the most significant challenge in design of electronic cooling systems. In order to overcome this, researchers have worked on various heat transfer enhancement techniques, e.g. use of partitions/fins Bauer and Wirtz, (2000), graphite/metal matrices Mehling *et al.,* (1999) and Kamimoto *et al.,* (1986). dispersed high-conductivity particles in the PCM Benmansour *et al.,* (2006), micro-encapsulation of PCM Velraj *et al.,* (1999) and Zalba *et al.,* (2004). and PCM-based heat sinks Pal and Joshi, (2001). Zheng and Wirtz (2000) designed a hybrid thermal energy storage(TES) and investigated the thermal properties of employed PCM. They optimized TES heatsink based on very small geometric and heat loading constraints using commercial optimizer. From the literature survey given, very little work focused on the optimization of TES heatsinks. The available optimization work was carried out under limited geometrical.

In the present study, TES is modeled using Lamberg, (2003) experimental TES setup in ANSYS. The numerical results is compared and validated with the melting temperature variation obtained by the established experimental work. Once validated, further ANSYS simulation was carried out for TES model with varying fin thickness, fin height and number of fins to obtain stabilization time and maximum operating temperature to average transition temperature difference. The data is used to train the ANN to predict stabilization time and maximum operating temperature to average transition temperature difference for new fin thicknesses, fin

Corresponding Author: Jeevan Kanesan, Dept of Electrical Engineering, Faculty of Engineering, University Malaya, Malaysia
E-mail: jievan@um.edu.my

height, number of fins and PCM volume. The ANN can automatically learn the complex relationships between those provided data and predict the TES model dimension and quality factors instantaneously thus eliminating complex mathematical model and time consuming numerical simulations to represent phase change process. The optimization of TES heatsink is carried out by embedding the trained ANN as a fitness function into genetic algorithms (GA). The objective of optimization is to maximize stabilization time and minimize maximum operating temperature to average transition temperature difference. Through this optimization, the optimal fin thickness, fin height and number of fins are obtained and used to build a new computer model of TES for numerical analysis.

Numerical Analysis:

ANSYS is employed to perform thermal analysis with phase change process. Phase change analysis is able to determine the temperature distribution at different points during the phase change and length of time for the phase change to occur. To analyze a phase change problem, a nonlinear transient thermal analysis is deployed. In nonlinear analysis, the latent heat of the material needs to be accounted for. Latent heat is the heat energy that the system stores or releases during a phase change. To consider for latent heat, the enthalpy per unit volume of the material is defined as a function of temperature. The enthalpy per unit volume, H_v in equation (1) which has units of energy per volume (J/m^3), is the integral of density multiply specific heat capacity in the function of temperature with respect to temperature. For solid or liquid state, the enthalpy per unit volume is derived as:

$$H_v = \int \rho C_p (T) dT \tag{1}$$

The specific heat capacity, C_p of the sample varies with temperature and determined according to Perkin-Elmer Dual Scanning Caloriemeter (DSC) measurements. From the DSC measurement, the relationship between specific heat capacity for melting and solidification of the PCM (n-octadecane) and temperature is determined. A preliminary numerical simulation was conducted on the experiment work by Lamberg, (2003) where two different kinds of TES heatsinks fabricated from solid aluminum 6061-T4 was used. The first type of heatsink is without fins (Storage A) and the other is equipped with two internal fins to enhance heat transfer inside the storage space (Storage B). The thickness of the heatsink storage space wall and fins are 1 mm. Figure 1 shows the two types of heatsinks analyzed. The heatsinks walls (left and right) were maintained at an isothermal condition by having hot plates on the left and right side of the wall. The remaining top and bottom walls were isolated from the environment with Styrofoam.

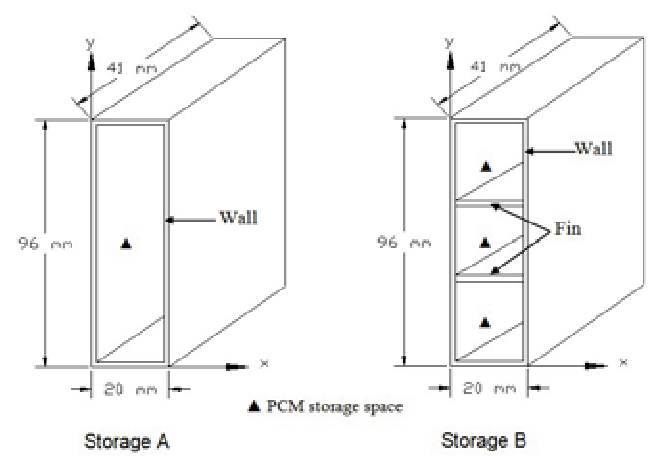


Fig. 1: TES heatsink configurations.

During the melting process, heat is initially transferred from the heatsink walls by conduction through the fin and the solid PCM, and later by also natural convection through the melted portion of the PCM. The velocity of the liquid paraffin in the cavity due to buoyancy forces is assumed to be constant. Thus, the natural convection effect in the cavity is simulated through an enhanced thermal conductivity, K'. Hence the enthalpy form for energy equation with initial and boundary conditions in melting process is given by:

$$\frac{\partial H}{\partial t} = \frac{k'\nabla^2 T}{\rho} \tag{2}$$

where H is the enthalpy, k' is the enhanced thermal conductivity, L is the length of the storage space, and D is the height of the storage space. The subscript i denotes initial condition and w the wall of heat storage. When PCM is completely solid, k' is the thermal conductivity of the PCM. At the liquid face k' is determined iteratively. The initial temperature imposed on the TES heatsink for melting is 10°C where as for solidification is 40°C. The natural convection effect that occurs in liquid fraction of PCM is simulated through an enhanced thermal conductivity, k'. The best assumed k' value will result in the closest match between the numerical and the experimental work by Lamberg, (2003). Once the best k' value is attained the numerical simulation is then carried out for a new set of fin thicknesses, fin height and number of fins shown in Table 1 to obtain the melting curve.

Table 1: Fin parameters utilized for numerical simulation.

No. of fins, N	Fin Thickness, W (mm)		Fin Height, D_f (mm)	
	Min	Max	Min	Max
3	5	30	3	18
4		20		
5		18		
6	4	15		

The maximum fin thickness is given by the height of the heatsink storage space divided by the number of fins (D/N) whereas the maximum fin height, D_f is given by the length of the heatsink storage space, L. The minimum values for fin thickness, W and D_f were arbitrarily selected.

ANN trained and GA optimization methodology for optimal TES:

In the present work, ANN is used to predict the quality factors of TES namely the stabilization time and maximum operating temperature to transition temperature difference. Thus the ANN will be trained with the error-back-propagation(EBP) network algorithm which has three layers of neurons known as input, hidden and output. The neurons in each layer are connected to each other through weighting functions. The input and output data are correlated by training the ANN using EBP network to form the network of input and the desired output. The TES heatsinks configuration such as fin thickness, fin height and number of fin are assigned as inputs where as stabilization time and maximum operating temperature to transition temperature difference are assigned as outputs. The trained ANN is used to predict TES heatsink's quality factors and the predicted values are compared and validated with the quality factors obtained from ANSYS simulation. Once a well trained ANN is obtained, it is then combined with GA. GAs are loosely based on the Darwinian theory of natural selection and survival of the fittest that was proposed by Holland (1975) and was first referred to as "genetic algorithms" by Bagley (1967). GA works by creating a population of individuals or chromosomes whereby each chromosome represents a possible solution to the given problem. In here the chromosomes are fin thickness, fin height and number of fins. The fitness function is the most crucial part of the GA. The present problem is treated as a dual objective optimization problem in order to maximize stabilization time and minimize the maximum operating temperature to transition temperature difference. Since both objectives are equally important for obtaining good quality factors for the TES heatsink, the quality factors are combined into a composite objective with equal weights in the GA fitness function. The fitness function evaluates each individual and assigns a fitness score according to how well the individual is suited to be a solution for the given problem. Then individuals with the best score will be selected through a *selection process*. The *selection process* can be based on the roulette wheel (Bagley,1967), ranking (Joines and Houck, 1994) or tournament selection process. The present study use GA toolbox available at http: //.eos.ncsu.edu/ pub/ simul/ GAOT/. The fin thickness, fin height and number of fins generated by GA is then fed into the trained ANN as input variables to predict TES quality factors namely stabilization time and maximum operating temperature to transition temperature difference. The predicted stabilization time, δt_s and maximum operating temperature to transition temperature difference, δT are then used in the fitness function to evaluate the optimization. The fitness function is given as:

$$Fitness\_Function = -\left(\left|\delta t_s - \delta t_s(avg)\right| + \left|\delta T - \delta T(avg)\right|\right) \tag{3}$$

From Equation 3, the predicted values are subtracted with the average stabilization time, $\delta t_s(avg)$ and average maximum operating temperature to transition temperature difference, $\delta T(avg)$ to obtain the fitness magnitude. The average stabilization time and average maximum operating temperature to transition temperature difference are determined manually by averaging stabilization time and maximum operating temperature to transition temperature difference. These average values are obtained using maximum and minimum fin thickness and fin height for each number of fins. The negative sign in the fitness function will ensure only non-positive fitness are generated. Therefore the ideal maximum fitness level is zero. The TES heatsink parameters in the first iteration coded as a chromosome is randomly generated by GA. The trained ANN then predicts the δt_s and δT values for each randomly generated chromosome. The predicted values are then evaluated by the GA fitness function. Once the fitness scores are tabulated and ranked, the top grade chromosomes (highest value fitness score) subsequently undergo the crossover and mutation processes. The population of newly recombined and mutated chromosomes becomes the new input variables for the trained ANN which then predicts TES quality factors for the new iteration in GA. GA will continue to iterate the fitness function value until the fitness function value converges to a maximum value. The converged result will yield to the optimal TES quality factors and optimal TES heatsink physical parameters respectively.

RESULTS AND DISCUSSION

The enhanced thermal conductivity, k' for the liquid phase of n-octadecane(PCM) has to be determined by conducting 2-D ANSYS simulation for arbitrarily selected enhanced thermal conductivity values and compared with the experimental results as shown in Figure 2. The constants used in the experimental work Lamberg, (2003) were utilized in the simulation. However, once n-octadecane melts and become liquid, a higher level of enhanced thermal conductivity is utilized to simulate the natural convection occurring in liquid phase. The 2-D ANSYS simulation is repeated for different values of enhanced thermal conductivity for liquid n-octadecane and the results are displayed in Figure 2. From the results, it is found that the melting temperature curve of $k' = 1.6$ W/mK is the closest match to the experimental work by Lamberg, (2003). Thus the enhanced thermal conductivity of $k' = 1.6$ W/mK is taken to perform the 2-D ANSYS simulation for other TES heatsink configurations.

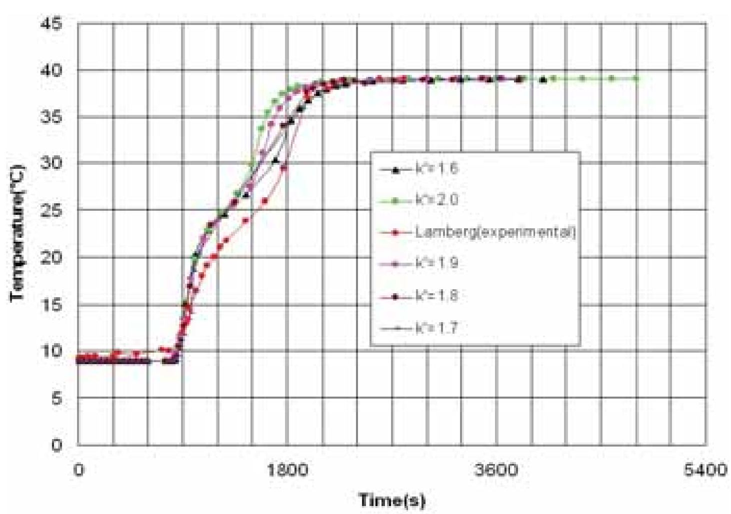
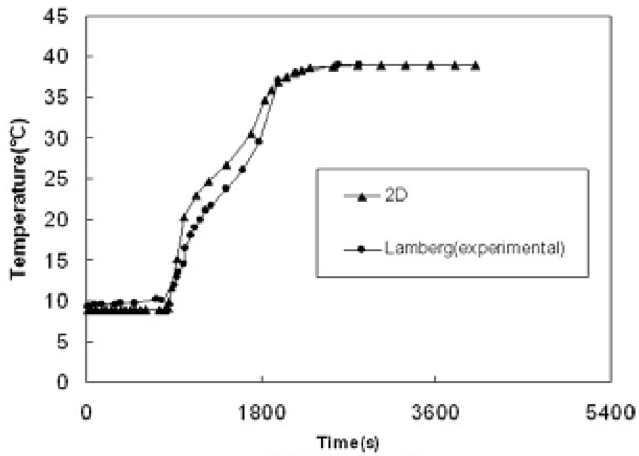
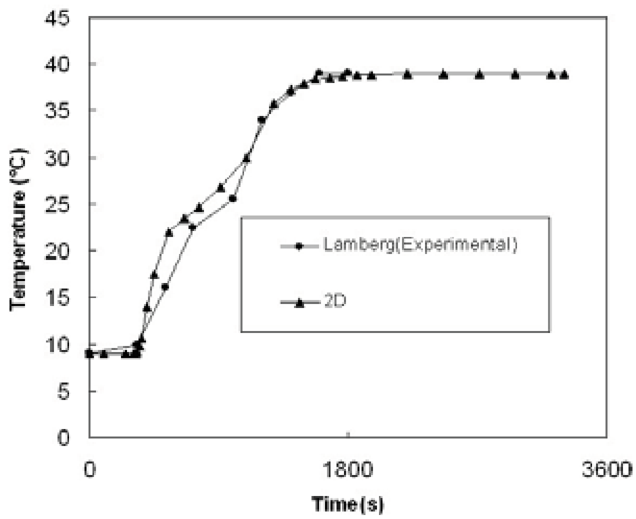


Fig. 2: Comparison of 2-D ANSYS simulation for different values of enhanced thermal conductivity with Lamberg, (2003).

By using enhanced thermal conductivity of $k' = 1.6$ W/mK obtained from previous simulation, a two dimensional (2-D) ANSYS simulation was carried out and compared with the existing experimental results by Lamberg, (2003) in order to validate the preliminary numerical simulation. The constants used in the experimental work were utilized in the simulation. The results obtained are shown in Figures 3(a) and (b).



(a) Storage A



(b) Storage B

Fig. 3: (a) and (b): Comparison of numerical simulation results with experimental results for two types of TES

From Figure 3(a), and 3(b), both the numerical and the experimental results show that there is no further rise in temperature beyond 1900s. The trends of the numerical simulation for both types of heatsinks compared well with the experimental work. With this, several more simulations were carried out with confidence for new range of fin thicknesses, fin height and number of fins (as shown in Table 1 previously). Approximately 192 set of heatsink quality factors were determined for various heatsink configurations. All these results were then used to train the ANN. The trained ANN was then used to predict the quality factors of the TES heatsink for a new set of heatsink parameters. ANN is used for predicting values within the given range of parameters in Table 1 in which ANN has been trained. Table 2 shows the ANN prediction and the numerical simulation results for selected number of fins, fin height and fin thickness. The final results show that ANN predictions for stabilization time, δt_s are within 4% of error and the maximum operating temperature to transition temperature difference, δT were within 0.5% in comparison with the numerical analysis results. In order to optimize TES heatsink, the trained ANN which can predict quality factors accurately is embedded in GA. The convergence of fitness function of GA optimization is shown in Figure 4. The fitness function score converged at -0.006952 after 85 generations. The optimal TES heatsink physical parameters at the converged fitness score is: Number of fins, N=4; Fin height, D_f=5.61mm; Fin width, W=16.98mm.

Table 2: Comparison between ANN predicted results and ANSYS simulation results.

No. of fins, N	Fin height, D_f (mm)	Fin thickness, W (mm)	δt_s (s)		% Error	δT (°C)		% Error
			ANSYS	ANN		ANSYS	ANN	
3	4.50	8.75	1120.3	1090.7	2.65	15.36	15.34	0.13
4	10.50	11.00	839.16	817.7	2.56	15.06	15.03	0.20
5	13.50	13.75	778.32	752.71	3.29	14.91	14.87	0.27

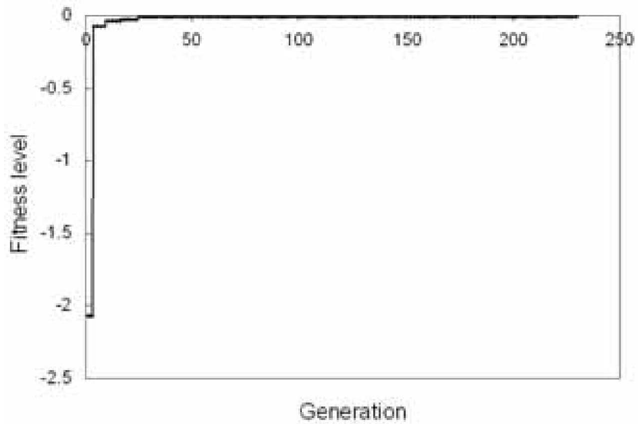


Fig. 4: Evolution of fitness function score.

A computer model based on optimized TES heatsink physical parameters, is then built in ANSYS to compare the ANN predicted GA optimized values for δt_s and δT. The result of this comparison is shown in Table 3(a). The ANN trained GA optimized results show that the optimized values for δt_s and δT were found to be 2% and 0.327% off of the computer simulation results respectively. The results clearly indicate that a well trained ANN combined with GA can be used to optimize TES heatsink quality factors with confidence. Finally the optimized TES heatsink quality factors are compared with the finless (Storage A) and two fins (Storage B) TES heatsink quality factors. Table 3(b) shows the results of this comparison. From Table 3(b), the stabilization time obtained from optimization recorded significant drop of 64.12% and 58.45% in comparison with stabilization time of Storage A and Storage B heatsinks respectively. Optimal maximum operating temperature to transition temperature difference recorded 8.207% and 6.015% reduction compared to maximum operating temperature to transition temperature difference of Storage A and Storage B heatsinks respectively.

Table 3: (a) and (b) Optimized δt_s and δT results

: ANN+GA compared to ANSYS

Optimized δt_s (s)		% Error	Optimized δT (°C)		% Error
ANN+GA	ANSYS		ANN+GA	ANSYS	
789.310	805.428	2.001	14.953	15.002	0.327

(b): ANN+GA optimized TES heatsink % of improvement from experimental results

TES heatsink quality factors	ANN+GA optimized heatsink	Experimental results [10]	
		Storage A	Storage B
δt_s (s)	789.310	2200	1900
δT (°C)	14.953	16.29	15.91
ANN+GA optimized TES heatsink % of	δt_s	64.12	58.45
improvement from experimental results	δT	8.207	6.015

Conclusion:

In the design and optimization of TES heatsink, the ANN predictions on the stabilization time and maximum operating temperature to transition temperature difference found to compare well with the ANSYS 2D simulated results. The final results show that ANN predictions for stabilization time were within 3.5% of error and the maximum operating temperature to transition temperature difference were within 0.4% in comparison with the simulated results. The ANN trained GA optimization results show that optimal stabilization time is almost 2% error and the optimal maximum operating temperature to transition temperature difference produced within 0.4% error in comparison with the ANSYS results. The computational time required for the optimization to produce the optimal heatsink quality factors is within 2 minutes using Pentium 4 (1 Gigahertz). GA optimized the TES heatsink quality factors with more than 55% drop in stabilization time and within 9% reduction in maximum operating temperature to transition temperature difference in comparison with stabilization time of finless TES heatsink and two fin TES heatsink. Artificial neural network was used to predict the stabilization time and thermal resistance for a given range of fin thickness, fin height and number of fins. ANN trained GA optimization clearly made significant improvement in the final TES heat sink design. This study shows that by combining ANN and GA a superior tool for optimization is realized.

Nomenclature

C_p	Specific heat capacity, kJ/kg°C	ρ	Density, kg/m^3
D_f	Fin thickness, mm	t	Fin height, mm
H	Latent Heat, J/kg	T_m	Solidification temperature, °C
k	Thermal conductivity, W/m°C	T_{tr}	Transition temperature, °C
N	Number of fins		

REFERENCES

Bagley, J.D., 1967. The Behavior of Adaptive Systems Which Employ Genetic and correlation Algorithms,Dissertation Abstracts International, 28(12).

Bauer, C., R. Wirtz, 2000. Thermal characteristics of a compact, passive thermal energy storage device, in: Proceedings of the 2000 ASME IMECE, Orlando, USA.

Benmansour, A., M. Hamdan and A. Bengeuddach, 2006. Experimental and numerical investigation of solid particles thermal energy storage unit, Appl. Therm. Eng., pp: 513-518.

Holland, J.H., 1975."Adaptation in Natural and Artificial Systems". University of Michigan Press, Ann Arbor, MI.

Joines, J.A., & C.R. Houck, 1994. On the Use of Non-Stationary Penalty Functions to Solve Nonlinear Constrained Optimization Problems with GA's. IEEE Transactions on Evolutionary Computation, 7(5): 445-455.

Kamimoto, M., Y. Abe, K. Kanari, S. Swata, T. Tani and T. Ozawa, 1986. Heat Transfer in Latent Heat Thermal Storage Units Using Pentarythritol Slurry, Thermal Energy Storage, World Congress of Chemical Engineering, Tokyo, Japan.

Lamberg, P. and K. Siren, 2003. "Approximate analytical model for solidification in a finite PCM storage with internal fins," Applied Mathematical Modelling, 27: 491-513.

Leoni, N. and C. Amon, 1997. Transient Thermal Design of Wearable Computers with Embedded Electronics Using Phase Change Materials, *ASME HTD*, 343: 49-56.

Mehling, H., S. Hiebler, S. Ziegler, 1999. Latent heat storage using a PCM-graphite composite material: advantages and potential applications, In: Proceedings of the 4th Workshop of IEA ECES IA Annex 10, Bendiktbeuern, Germany.

Pal, D. and Y.K. Joshi, 2001. Melting in a side heated tall enclosure by a uniformly dissipating heat source, Int. J. Heat Mass Transfer., 44: 375-387.

Velraj, R.,R.V. Seeniraj, B. Hafner, C. Faber and K. Schwarzer, 1999. Heat transfer enhancement in a latent heat storage system, Sol. Energy, 65(3): 171-180.

Zalba, B., J.M. Marin, L.F. Cabeza and H. Mehlin, 2004. Free-cooling of building with phase change materials, Int. J. Refrig., 27: 839-849.

Zheng, N. and R.A. Wirtz, 2000. Methodology For Designing A Hybrid Thermal Energy Storage Heat Sink, *ASME*., 2-16-2-10.