INVESTIGATION OF INTRINSIC DYNAMIC CHARACTERISTICS IN AN OSCILLATING HEAT PIPE

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Key words: oscillating heat pipe, conjugate heat transfer, nonlinear behavior, frequency resonance.

ABSTRACT

Conjugate heat transfer devices based on oscillating phenomenon allow thermal instability to play a crucial role in thermal management. This study proposed and tested a hollow cylindrical oscillating heat pipe (OHP) for managing waste heat sources. Deionized water was filled as a working medium at ratios of 10%–90%. Experiments were conducted with heat inputs 10–120 W; the performance was dependent on the features of self-sustained oscillations. Dry-out was found only under low filling conditions, and this operating fault can be avoided by increasing the working medium. A medium level of approximately 50% is optimal.

The intrinsic thermal instability related to the performance of an oscillating thermal design has attracted considerable academic interest. Simplifications and assumptions of traditional modeling approaches render them unsuitable for probing the dynamic characteristics of such thermal designs. A nonlinear autoregressive exogenous (NARX) modeling based on machine learning techniques was introduced to identify the causality of the heat transfer mechanism of the OHP. The discrete models estimated using the NARX modeling accurately simulated OHP dynamics, which were further revealed through spectrum analysis. Energy excitation, shown as frequency resonances, was distinctly related to OHP performance.

I. INTRODUCTION

As the functions of electronics have become more diverse, the miniaturization and congregation of components have resulted in high power densities in the electronics industry. This led to thermal management becoming a primary issue in industrial application. To meet the requirements of increasing power densities of electronic devices or confined spaces, various heat transfer designs were developed to maintain the reliability and performance of products (Mangini, 2015; Bigham, 2015). Akachi (Akachi, 1990) proposed a promising heat pipe, called an oscillating heat pipe (OHP), that can operate without a capillary wick structure and be simply fabricated from a capillary metal tube bent into turns. With their excellent conjugate heat transfer and operational flexibility, OHPs have attracted many in the fields of industry and academia (Faghri, 2012; Vo, 2020). The development of technologies creates new challenges, which makes it necessary to evaluate the maneuverability potential of OHPs. In OHPs, the internal tube diameter is sufficiently small to cause capillary force to form both liquid slugs and vapor plugs in the tube, resulting in pressure pulsations to drive slug movement (Qu, 2012; Han, 2016). Heat transfer from heated to cooled areas is caused by rapid transition of vapor bubble growth and collapse, and the induced thermal instability influences the capacity of an OHP.

Both sensible heat and latent heat combine to form net heat transfer. Sensible heat dominates the overall heat transfer, because the slug flow regime dominates the flow field. The proportion of latent heat increases as the slug flow converts to annular flow, improving performance (Burban, 2013; Kwon, 2015; Spinato, 2016). Studies have visualized changes of flow patterns to elucidate the operational principles of loop flow, differentiated isolated bubbles, expansion and coalescence of bubbles, slug flow, and annular flow. Through flow virtualizations, many studies have revealed the nonequilibrium heat transfer of OHPs (Rao, 2013; Manzoni, 2016; Kim, 2017). Through comparison of observations and synchronous measurements, the transition of flow patterns and the oscillating features of OHPs have been clarified.

OHPs are suitable for applications of high heat loads. Because the input heat is the driving source, no flow oscillation exists below a critical level of heat input. However, vapor bubbles will be generated at a high rate if the heat load increases to a high level. Such induced instability affects the propulsion to all OHPs. However, it is difficult to adjust this intrinsic feature through common methods. At extremely high heating
Fig. 1. (a) Photo and (b) schematic of the established setup of the designed OHP system employed for thermal analysis.

conditions, the vapor plugs enlarge in the evaporator, leading to local dry-outs (Lin, 2011; Chan, 2015; Yin, 2016). Consequently, the performance limit of OHPs is reached at this critical heat flux (Nuntaphan, 2010; Ji, 2011; Goshayeshi, 2016). Recently, theoretical analysis and mathematical derivation in OHP study have attempted to simplify approaches. Modeling with semiempirical correlations has become the most promising approach (Tseng, 2016; Ebrahim Dehshali, 2018). Researchers acknowledge that these methods are only approximations, because little is known about the operating mechanism of OHPs. Statistical approaches based on response surface methodology were employed to optimize OHPs (Khalajzadeh, 2011; Olabi, 2013). In contrast to conventional methods, the interaction among process variables in response surface methodology can be determined through statistical techniques. They provide reference and partial validity but do not accurately describe practical OHP dynamics.

Random time series data, including the oscillating temperature responses of an OHP, occur in physical phenomena, and it is difficult to find an explicit mathematical formula to describe their properties (Shuai, 2017; Deb, 2017). The efficient implementation of machine learning techniques in a dynamic system presents many research challenges. A prerequisite to the investigation of nonlinear systems is a method of characterizing the dynamic behavior of such systems from input–output (I/O) measurements, and this has been the objective of nonlinear modeling. Artificial neural networks (ANNs) have been widely implemented to investigate a chaotic system with large quantities of random I/O time series data (Flores, 2012; Babu, 2014; Tak, 2018; Hu, 2020). A typical ANN consists of a number of simple processing units interconnected to form a complex network. Layers of such units are arranged so that data is entered at the input layer and passes through either one or several intermediate layers before reaching the output layer. ANNs provide an option to address complex and ill-defined problems and are used in many engineering applications, because they offer more reasonable solutions. Based on radial basic function neural networks, a nonlinear autoregressive exogenous (NARX) modeling suitable to chaotic system identification in the discrete-time domain was proposed (He, 2016; Asgari, 2016; Siong Tok, 2017; Zhang, 2020).

This study introduced a NARX modeling to train massive quantities of temperature data to obtain the causality of the
cooling process of an oscillating heat pipe (OHP). Nonlinear generalized frequency response functions (GFRFs) derived from the discrete-time NARX models were used to illustrate the OHP resonance dynamics. Thus, resonances became ridgets and antiresonances became valleys, allowing for further understanding of the energy aggregation and expansion in the OHP.

II. EXPERIMENTAL

The OHP equipped in an exhaust gas heat exchanger was designed to remove thermal energy from a stationary diesel or gas engine's exhaust stream and convert it into a valuable energy source. Fig. 1 illustrates the experimental setup, which consisted of the OHP, an electrical power supply, a temperature data logger, and a computer. The geometric configuration of the OHP was symmetrical, and the entire pipe was made of copper capillary with an inner diameter of 3 mm and a wall thickness of 1 mm. The dimensions of the OHP were 135 mm × 135 mm × 320 mm, and the bending radius of the 16 U-turns in both ends was 8 mm. A 70-mm heating section was covered by an isolating tap, and the rest of tube as the cooling section was exposed to the environment. An electrical power supply unit (GITEK, model GR-11H12H) was used to apply a heat source through a Ni–Cr coil (OMEGA, model NIC80) wrapped on the heating section with an equal interval of 3 mm. A three-way valve mounted on the OHP was to allow for vacuuming and filling of the OHP with working medium using a syringe. The vacuum of the OHP was kept at 10⁻² torr before the working medium was filled. Deionized (DI) water was chosen for the working medium for safety considerations and its high Merit number compared with other cooling media. The primary parameter, the filling ratio, used to indicate OHP performance was a ratio of DI water fill volume to the entire void volume of the tube. The DI water loaded into the OHP was weighed using an electronic microbalance (SHINKO, model HT-220E), with minimal uncertainty of ±0.01g.

The OHP was tested in vertical bottom heating mode without any auxiliary cooling design. A range of stable voltage output (2–220 V) was acquired by regulating the electrical power supply unit. After the heat was absorbed by the heating section, it was directly transferred throughout the cooling section through conduction of the solid tube and convection of the working medium and finally released to the environment. To the cooling section, five K-type thermocouples connected to a data logger (GRAPHTEC, model GL240) were attached from L1 to L5 at an interval of 50 mm to measure the corresponding wall temperature responses (T1–T5) with an accuracy of ±0.5°C. To assess OHP performance, the thermal resistance can be obtained as follows:

$$R = \left( \bar{T}_1 - \bar{T}_5 \right) / Q_{\text{input}},$$

where $Q_{\text{input}}$ is the heat input, and $\Delta T = T1 - T5$ is the temperature drop of the cooling section (overline represents mean value). Every experiment was conducted for exactly 1 h, and all the temperature data were sampled at a time interval of 0.05 s under a 26°C ± 1°C environment. To identify OHP performance, a range of conditions was tested, with filling ratios of 10–90% and heat inputs of 10–120 W.

III. APPROACH

The operating mechanism of the OHP is based on flow oscillation, which comprises known and unknown physical parameters and dominates the mechanism of heat transfer. NARX modeling was introduced to identify the time-dependent relationship of the temperature responses of the cooling section of the OHP using actual measurements without a priori knowledge of the equations of motion. A NARX modeling is a recurrent dynamic network with feedback connections and universal approximation capabilities and is used in most scientific fields (He, 2014; Solares, 2016; Banihabib, 2017; Gu, 2018). It has three layers: input layer, output layer, and hidden layer. Neurons in the input layer act as buffers for distributing the input vector $x(t) = [x_1(t), x_2(t), x_3(t), ..., x_n(t)]$ to neurons in the hidden layer. Each neuron in the hidden layer sums its inputs after weighting them using scalar weights and assigned unity values. However, it is connected to the output neurons through different weights $w_k(t) = [w_{k1}(t), w_{k2}(t), w_{k3}(t), ..., w_{kn}(t)]$. For each neuron, the distance between the input and its center is determined by applying the radial basis function, and the resulting scalar is passed through a nonlinearity function. Thus, the output layer yields a vector $y(t) = [y_1(t), y_2(t), y_3(t), ..., y_n(t)]$ for $n$ outputs through a collection of the outputs of the hidden neurons to obtain the ultimate output as follows:

$$y = w_0 + \sum_{p=1}^{q} \sum_{q=1}^{Q} w_{pq} \phi_q(x) + e(t),$$

where $w_{pq}$ is the hidden-to-output weight, $e(t)$ is the modeling error, and the radial basis function $\phi_q(x)$ is a Gaussian-type function, represented by

$$\phi_q \left( \| x(t) - c_q \| \right) = \exp \left[ -\frac{1}{2\sigma^2} \sum_{q=1}^{Q} \| x(t) - c_q \|^2 \right],$$

where $\sigma$ is the kernel estimator, and $c_q$ represents the location parameters that determine the kernel positions. Both $\sigma$ and $c_q$ are predetermined during a network training procedure. The model structure was detected by the orthogonal least squares algorithm (Chen, 1991; Wang, 2016; Li, 2017). A single-input single-output (SISO) NARX model can be expressed as follows:
where $x(t)$ and $y(t)$ are the system input and output, respectively; $F[\cdot]$ is a vector-valued nonlinear function; $\alpha$ is a constant vector term; $\ell$ is the degree of nonlinearity; $d$ is the system time delay; and $n_x$ and $n_y$ are the maximum lags for the input and output, respectively.

Conservative principles are crucial to prevent excessive estimations in nonlinear system diagnosis. The model provides an indication of each term’s contribution through the evaluation of an effective term criterion, the error reduction ratio (ERR) (Sarrigiannis, 2014; Hafiz, 2020), defined as follows:

$$
ERR_i = \frac{\sum_{j=1}^{N} g_i^2 s_i^2(t)}{\sum_{i=1}^{N} y_i^2(t)} \times 100\%,
$$

where $N$ is the number of observations; $s_i$ is the term of an auxiliary model constructed so that the term is orthogonal to the data records; and $g_i$ is the coefficient of $s_i$. 

Fig. 2. Temporal variations of T1, T3, and T5 for a 10%-filled OHP at heat inputs of (a) 10 W, (b) 20 W, (c) 60 W, and (d) 100 W.
The root-mean-square error (RMSE) (Busch, 2014; Ho, 2018) was used as a criterion to evaluate the convergence of the learning process. The RMSE of one training epoch was defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y'_i)^2},$$

where $n$ is the number of observations, $y_i$ is the $i$th measured value, and $y'_i$ is the simulated value for $y_i$.

To reveal the oscillating characteristic of a tube flow, the transient signals of temperature responses must be analyzed by spectrum. The proposed GFRFs, defined as multiple Fourier transforms of the kernels (Amenabar, 2017; You, 2020), can capture both linear and nonlinear characteristics of systems and are critical in the diagnosis of system behavior in the

Fig. 3. Temporal variations of $T_1$, $T_3$, and $T_5$ for a 50%-filled OHP at heat inputs of (a) 10 W, (b) 20 W, (c) 60 W, and (d) 100 W.
frequency domain. This method is much more effective, because each frequency response function can be derived directly from the parametric model fitted to the measured signals, significantly reducing the computational burden. Consider a Volterra series (Gruber, 2012; Cheng, 2017; Villani, 2019) given by

$$y(t) = \sum_{n=1}^{\infty} y_n(t),$$  \hfill (7)

where the $n$th-order output of $y_n(t)$ is given by

$$y_n(t) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} h_n(\tau_1, \ldots, \tau_n) \prod_{i=1}^{n} x(t - \tau_i) \, d\tau_i, \quad n > 0,$$  \hfill (8)

where $h_n(\tau_1, \ldots, \tau_n)$ is the $n$th-order impulse response, and $\tau$ is the time lag of the system. The multiple Fourier transform of $h_n(\tau_1, \ldots, \tau_n)$ yields the $n$th-order GFRF, defined as follows:
the inverse Fourier transform of Eq. (11):

\[ H_n(f_1,\ldots,f_n) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} h_n(\tau_1,\ldots,\tau_n) e^{j2\pi(f_1\tau_1+\cdots+f_n\tau_n)} d\tau_1,\ldots,d\tau_n, \] \tag{9}

Conversely, the nth-order impulse response is derived from the inverse Fourier transform of Eq. (11):

\[ h_n(\tau_1,\ldots,\tau_n) = \frac{1}{(2\pi)^n} \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} H_n(f_1,\ldots,f_n) e^{j2\pi(f_1\tau_1+\cdots+f_n\tau_n)} d\tau_1,\ldots,d\tau_n, \] \tag{10}

Substituting Eq. (11) into Eq. (9) and performing multiple integrals on \( \tau_1,\ldots,\tau_n \) gives:

\[ y_n(t) = \frac{1}{(2\pi)^n} \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} H_n(f_1,\ldots,f_n) \prod_{i=1}^{N} X(f_i) e^{j2\pi f_1 t}, \] \tag{11}

where \( X(f) \) is the Fourier transform of the input \( x(t) \). When the multiple Fourier transform is applied to both sides, a familiar form at the frequency domain is obtained as follows:

\[ y_n(f_1,\ldots,f_n) = H_n(f_1,\ldots,f_n) = \prod_{i=1}^{N} X(f_i), \] \tag{12}

where \( h_n(\tau_1,\ldots,\tau_n) \) and \( H_n(f_1,\ldots,f_n) \) are equivalent transfer function representations in the time and frequency domains, respectively, for the nth-order homogeneous subsystem, and both are independent of the input excitation. Because frequency response functions of real systems are conjugated when the signs of all arguments are changed, in the equation

\[ H_n(-f_1,\ldots,-f_n) = H_n^*(f_1,\ldots,f_n), \] \tag{13}

the asterisk donates complex conjugate holds. The symmetry and conjugation properties can now be used to display the frequency response functions \( H_n(f_1,\ldots,f_n) \). Here, \( x(t) \) is assumed to be the sum of \( K \) sinusoids required to compute the GFRFs, represented as follows:

\[ x(t) = \sum_{k=1}^{K} A_k e^{j2\pi f_k t}, \] \tag{14}

where \( A_k \) is the amplitude. Through substitution of Eq. (15) into Eq. (9), the nth-order output can be expressed as follows:

\[ y_n(t) = \sum_{k=1}^{K} \cdots \sum_{k_i=1}^{K} A_{k_1,\ldots,k_i} H_n(f_{k_1,\ldots,k_i}) e^{j2\pi(f_{k_1}+\cdots+f_{k_i}) t}. \] \tag{15}

If \( K = n \) and \( A_k = 1 \) for all \( k = 1, 2, \ldots, n \), the Fourier transform of Eq. (17) becomes a sum of delta functions, represented as

\[ y_n(t) = \sum_{k=1}^{n} H_n(f_{k_1,\ldots,k_n}) e^{-j2\pi(f_{k_1}+\cdots+f_{k_n}) t}, \] \tag{16}

Higher-order GFRFs can be derived using the aforementioned expressions. A general form for higher-order GFRFs can be expressed as

\[ \sum_{L=0}^{K} \sum_{\beta=0}^{L} c_{\beta L}(\ell_{1},\ldots,\ell_{\beta}) e^{\imath 2\pi(f_{\ell_{1}}+\cdots+f_{\ell_{\beta}} t)} \sum_{\gamma=0}^{L} \sum_{\alpha=0}^{\gamma} c_{\alpha \gamma}(\ell_{1},\ldots,\ell_{\alpha}) e^{\imath 2\pi(f_{\ell_{1}}+\cdots+f_{\ell_{\alpha}} t)} H_{n-q,p}(f_{\ell_{1},\ldots,\ell_{p}}), \] \tag{18}

Thus, an asymmetric nth-order GFRF can be obtained by the regressive relation as
To assess the proposed OHP, a wide range of testing conditions was considered in the experiment. Specific temperature responses along the cooling section were measured, in which T1, T3, and T5, representing the starting, middle, and terminal locations (i.e., L1, L3, and L5) of the cooling section, were chosen for analysis. At a low filling ratio of 10%, T1 and T3 increased slowly, but T5 remained at the initial value with a heat input of 10 W. This indicated that the heat was too low to vaporize such a low fill of working medium, and the heat dissipated to the environment before transferring to L5 (Fig. 2(a)).

These temperature responses without distinct oscillations showed that the cooling process was dominated by heat conduction, causing high thermal resistance. When the heat input was increased to 20 W, more severe oscillations were found in T1 and T3, and tiny fluctuations appeared in T5. This indicates that the heat input was sufficient to vaporize the working medium but could not sustain continuous flow circulation (Fig. 2(b)). T5 oscillated with the heat input; the oscillating amplitude of T5 became larger than those of the other temperature responses when the heat input reached 100 W (Fig. 2(c)). As heat input increased, reciprocate temperature perturbations occurred more frequently. Superior thermal performance was evidenced by the existence of distinct flow oscillations throughout the cooling section. Abruptly changing temperatures with
larger amplitudes and lower frequencies representing extremely unsteady flow transients were caused by the lacking of working medium (Fig. 2(d)). At a medium filling ratio of 50%, no distinct temperature perturbations were detected, and $T_5$ remained stagnant at 10 W (Fig. 3(a)), similar to Fig. 2(a). Random temperature responses with larger amplitudes were measured throughout the experiment as the heat input exceeded 20 W (Fig. 3(b)). All temperature responses showed a similar oscillating trend when the heat input reached 60 W (Fig. 3(c),(d)). Under this condition, consistently unsteady flow oscillations existed throughout the cooling section. When the working medium was filled to an extremely high ratio of 90%, the starting threshold of heat input increased (Fig. 4(a),(b)). In contrast to the results of the low and medium filling ratios, conjugate heat transfer was noticeably suppressed by the excessive working medium at heat inputs less than 30 W. Compared with the 50%-filled OHP, lower performance was predicted because of larger temperature drops observed in the 90%-filled OHP (Fig. 4(c),(d)).

Fig. 5 presents a comparison of OHP performance under different operating conditions. The temperature drop used to estimate the thermal resistance was obtained from a duration of 30 min (observations 30001–66000), in which high thermal resistances were found at low heat inputs regardless of the filling ratio. When the OHP primarily operated through latent heat transfer, the thermal resistance decreased with heat input. At filling ratios of 30% and lower, the thermal resistance abruptly increased to 110 W, because the liquid was prohibited from entering the heating section, and a complete dry-out was found at 120 W. However, these failures can be avoided by additional filling with working medium. The 50%-filled OHP showed the lowest thermal resistance in normal operation, ensuring a medium filling ratio is optimal for this heat pipe configuration. Moreover, all the filling conditions tested for the OHP were appropriate for a heating range of 10–100 W, and the heating limit can be extended to at least 120 W with at least a medium filling ratio. To investigate the dynamic characteristics of the OHP, the same duration of measurement was selected for modeling, in which $T_1$ and $T_5$ were set as the input and the output, respectively.

Fig. 7. Correlations of the measured and simulated $T_5$ values for a 50%-filled OHP at heat inputs of (a) 20, (b) 60, and (c) 100 W.
Fig. 8. Variations in energy resonance in a 50%-filled OHP at heat inputs of (a) 20, (b) 60, and (c) 100 W.
With appearance of temperature perturbations, the OHP was shown to be normally actuated at 20 W. Heating levels of 20, 60, and 100 W, designated as low, medium, and high heat inputs, are discussed. A second-order model with simple structure terms was the first consideration. One hidden layer and three hidden neurons were set for effective neural network training with less computational time. The maximum time lags for input and output were appropriately set as 5 and 30 through trial and error. Thus, 630 possible combinations of structure terms (i.e., 35 single and 595 square terms) were obtained. Using the orthogonal least squares algorithm and the model validation test, the 15 most essential terms were estimated and ranked. These models, structured by I/O temperatures, represent real-time variation in thermal energy throughout the cooling process; \( T_S(t-1) \) and \( T_S(t-2) \) were shown to be the two most contributed terms, occupied the majority of contributions in each model structure. This indicates that self-prediction is essential to the NARX modeling to such nonlinear thermal designs. These models were in good agreement with measurements (Fig. 6). Tiny RMSE values for these models were obtained as 0.56°C, 1.49°C, and 2.36°C, and over 95% of simulated results were within a relative error of ±30% (Fig. 7). This reasonable result demonstrates that the proposed modeling strategy is suitable for long-term diagnosis of a chaotic system.

The second-order GFRFs derived from the aforementioned models presented the resonant features of an optimally filled OHP to clearly reveal the nonlinear phenomena of conjugate heat transfer. These frequency features, illustrating the effect of thermal instabilities on the pipe flow, are excitations of the heat transfer mechanism converting input frequencies into output frequencies. In Fig. 8(a), four main frequency ridges appear as functions listed on the responding surface, indicating the OHP dynamics consist of both linear and nonlinear features at a threshold of heat input. Functions \( f_1 = \pm 0.5 \text{ Hz} \) and \( f_2 = \pm 0.5 \text{ Hz} \) are linear features, showing that energy aggregates near ±0.5 Hz. However, the nonlinear features shown as resonances near \( f_1 + f_2 = \pm 1.2 \text{ Hz} \) were generated by energy transferring to these frequencies. Theoretically, the negative frequency axis shown in this figure is just a mirror image of the positive frequency axis. When increasing the heat input, the linear features become indistinct, and the nonlinear resonance range expands. The enhanced thermal instability caused resonances to fluctuate by 1.8–2.7 Hz as the heat input increased from 60 to 100 W (Fig. 8(b),(c)). These resonances corresponded to a periodic feature around 0.370–0.556 s in flow oscillations. Output energy at these frequency ranges were produced by nonlinear effects in the heat transfer mechanism of the OHP causing a strong intermodulation between frequencies. Although there were many cross-ridges, the main ridges dominated the effects on energy transfer. Moreover, the entire gain spectrum was entirely increased with more thermal energy input.

V. CONCLUSIONS

An OHP with a hollow cylindrical configuration used for large heat sources was tested successfully. This OHP without an auxiliary heat source is a simplified thermal design that can be efficiently operated under various conditions. Good flexibility and reliability in the practical application of the OHP were confirmed by this study. Experiments indicated that the optimal filling ratio of this OHP is approximately 50%.

Flow circulation throughout the cooling process with consistently multiperiodic oscillations characterized and influenced OHP performance. Full transient flow oscillation increased thermal convection and thus reduced the thermal resistance. To investigate the intrinsic features of the OHP, a modeling strategy combining time and frequency domain was introduced. This more realistic NARX modeling produced results consistent with practical observations with several algorithms. More than 95% of simulated results were within a relative error of ±30%.

The introduction of GFRFs provided a method to capture and explain the nonlinear frequency domain phenomena in various dynamic states of the OHP. Both linear and nonlinear features of conjugate heat transfer of the OHP can be distinctly characterized by frequency resonances. With more thermal energy input into the OHP, the nonlinear resonance expanded, and the gain spectrum increases. This quantitative analysis based in theory illustrated the intrinsic features of the OHP as key to such oscillating thermal designs.

CONFLICT OF INTEREST

The author herein declares no conflicts of interest that could prevent the publication of this article.

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REFERENCES


Yin, D., H. Wang, B. H. Ma and Y. L. Ji (2016). Operation limitation of an