ScienceDirect

Applied Thermal Engineering
Volume 228, 25 June 2023, 120558

Research Paper

Nonintrusive heat flux quantification using acoustic emissions during pool boiling

Christy Dunlap, Hari Pandey, Ethan Weems, Han Hu

Show more

Share Cite

https://doi.org/10.1016/j.applthermaleng.2023.120558
Get rights and content

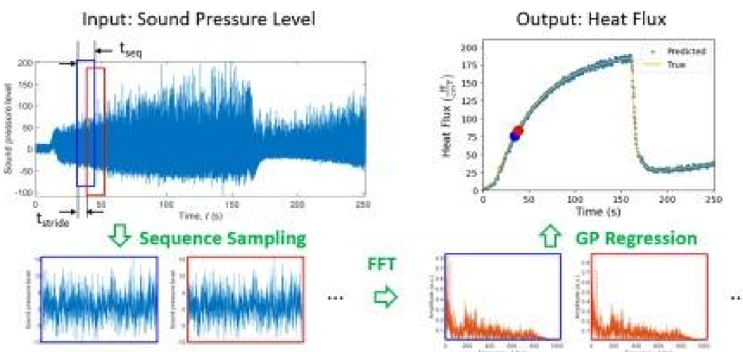
Highlights

- Machine learning models are developed for sound-based boiling heat flux prediction.
- Two feature extraction and three regression algorithms are tested and compared.
- The FFT-GPR model yields a MAPE of 4.5% and an R^2 score of 0.999.
- The temporal sequence length plays a critical role in heat flux prediction.
- Low-frequency acoustic emissions (<512 Hz) are important for the predictions.

Abstract

Monitoring two-phase cooling systems is crucial to avoid thermal runaways and device failures. Nonintrusive monitoring methods using remote sensing, e.g., optical and acoustic sensors are desired to avoid interfering with bubble dynamics and ease replacement. Compared to image-based technologies, sound-based sensors are cheaper and do not require the same environment as cameras. Acoustic signals during pool boiling have been used to identify boiling states, but acoustic-based quantitative predictions have been challenging. The present work presents a machine learning framework to determine the heat flux during pool boiling using acoustic signals captured through a hydrophone. This framework investigates and compares the performance and computational cost of six machine learning models by coupling two feature extraction algorithms (fast Fourier transform and convolution) and three different regressors (multilayer perceptron, random forest, and Gaussian process regression). The fast Fourier transform-Gaussian process regression model is found to be the most promising with high accuracy and the lowest computational cost. A parametric study is performed to investigate the effect of the temporal length and sampling rates on the model predictions. It is found that the model's performance is improved with increasing temporal lengths of the acoustic sequences for all sampling rates. Acoustic features below 512 Hz are found to be most significant for heat flux predictions. For sampling rates beyond 512 Hz, the model performance is dictated by the temporal length of the acoustic sequences.

Graphical abstract



Download : Download high-res image (186KB)
Download : Download full-size image

Introduction

The rapid growth of electronic power output necessitates improved thermal management systems. Heat dissipation performance is essential to keep up with high power density applications, such as the subsystems within electric vehicles [1] or data centers [2]. Nucleate boiling heat transfer accommodates this pursuit while maintaining a relatively low superheat by taking advantage of the high latent heat of the working fluid and efficient vapor removal. Nevertheless, nucleate boiling is bounded by a practical limit known as the critical heat flux (CHF), beyond which the heat transfer mode changes to an unstable and far less efficient transition boiling regime [3]. A large fraction of the heater surface will be covered by a vapor film, causing significant heat transfer coefficient deterioration and potential device failures. It is thus critical to monitor and regulate the heat flux in boiling-based thermal management systems.

A variety of heat flux quantification methods have been implemented during pool boiling, including the Joule effect method, the gradient method, and the transverse thermoelectric effect method, among others [4]. The Joule effect method directly calculates the heat flux using the electrical voltage and current applied to the heating element and applies to systems with a large boiling surface area to total surface area ratio, e.g., boiling systems using thin-film heaters (ITO, titanium, and gold) [5], [6], [7]. Nevertheless, this method may be subject to large errors for non-uniform heating due to heat loss by spreading in the heater [7]. The electrical power input is more commonly used as a reference to estimate the heat loss rather than directly calculate the boiling heat flux. The gradient method measures the temperature difference across a layer of material with known thermal conductivity (k) and thickness to determine the temperature gradient at the boiling surface (∇T) and calculate the heat flux using Fourier's law ($\boldsymbol{q}=-k\nabla T$) [8], [9], [10]. A linear temperature profile will be obtained under steady-state conditions, which ensures accurate heat flux measurements with high sensitivities. Under transient conditions, inverse modeling of heat conduction with multiple temperature sensors will be required to account for the temporal and spatial nonlinearities [11]. The transverse thermoelectric effect method leverages materials with anisotropic thermal conductivity, electrical resistance, and thermoelectric coefficient to generate electric fields with a transverse component when heat passes through the principal axes of the materials [12]. This approach allows for ultra-fast response and is thus suitable for transient heat flux measurements. Nevertheless, both the gradient method and the transverse thermoelectric effect method are implemented as contact, surface-mounted sensors, which can be intrusive to boiling and may bring in challenges with sensor replacements. On the contrary, remote sensing technologies (e.g., optical sensing and acoustic sensing) are more promising for robust, non-intrusive heat flux quantification during boiling.

Visualization-based predictions of heat flux and other thermal properties have been explored for decades. Traditional boiling image analysis is focused on extracting physical parameters from boiling images, such as bubble diameter, bubble count, and departure frequency, and correlating these parameters with boiling thermal properties [13]. While this approach has contributed to advancing the fundamental understanding of bubble dynamics during boiling, it hasn't been demonstrated for reliable heat flux quantification due to the large fluctuations and uncertainties of the extracted parameters. Recent advances in machine learning have enabled accurate and reliable visualization-based boiling state classification [14], [15], [16], physics extraction [17], [18], as well as heat flux quantification [19], [20], [21]. Hobold et al. developed two machine learning models for heat flux quantification using boiling images, namely, i) convolutional neural networks (CNN), and ii) combined principal component analysis (PCA) and multilayer perceptron (MLP) [19]. Suh et al. developed a hybrid model for boiling heat flux prediction by concatenating the output from a CNN model trained on boiling images and an MLP model trained on bubble size and count extracted from boiling images and the hybrid model showed reduced error compared to the standalone CNN and MLP models [21]. Despite their success, visualization-based heat flux measurements are subject to two major challenges, which prevent their implementation in industrial product lines. First of all, optical imaging requires a line of sight to be constructed with proper illumination, transparent walls, etc. This is generally impractical in many thermal management systems. Moreover, data storage and transmission of images also bring challenges for real-time data analysis, especially when sampled at higher frequencies.

Compared to optical imaging, acoustic sensing is a light, low-cost, and easy-to-implement alternative. A variety of acoustic sensors have been leveraged in boiling studies, including acoustic emission (AE) sensors [22], [23], [24], [25], [26], hydrophones [27], [28], [29], [30], [31], and condenser microphones [32], [33], [34], [35], [36], [37]. AE sensors detect stress waves in solid materials and have been widely used in monitoring the mechanical properties of materials and structures. Hydrophones are immersed in the liquid pool and thus have a unique advantage in boiling studies by being placed as close to the boiler surface as possible. Condenser microphones provide remote measurements but also have greater noise which necessitates implementing microphone arrays for localizing the sources of sounds [38]. Existing boiling studies have used the raw signals from the acoustic sensors (sound pressure level) as well as frequency-domain analysis, including the probability density functions (PDF), power spectral density (PSD), auto-power spectral density, spectrogram, and discrete wavelet transform (DWT) to correlate acoustic signals with boiling characteristics. For example, Alhashan et al. used a pool boiling set-up with two acoustic emission sensors and correlated the acoustic emission energy, RMS, amplitude, etc. to the fluid viscosity and the bubble diameter [24]. Baek et al. monitored water boiling using an AE sensor and observed a quantitative relationship between AE parameters and the boiling heat flux. The AE hit number (i.e., the number of sound pressure levels beyond a preset threshold) is shown to increase with boiling heat flux [25]. Nishant et al. performed pool boiling experiments at different subcooling with synchronized optical-acoustic-thermal sensing and showed a sharp increase in the intensity of the audio signals at CHF [31]. Recent advances in machine-learning-aided signal processing have also led to progress in acoustic sensing. Acoustic sensing has been integrated with machine learning for a wide range of applications, including the classification of kinking and twinning behavior of alloys under compression tests [39], detection of valve conditions (cavitation, whistling, rattling) in heating systems [40], anomaly detection in a sliding bearing system [41], guitar effects recognition [42], and monitoring of gas–liquid mixing [43]. For acoustic sensing in boiling, Sinha et al. developed a CNN model to classify boiling regimes using acoustic signals from a hydrophone in the pool [29]. Similar to CNN models for speech and music classification, Sinha et al.'s model converted sound pressure levels from the hydrophone to spectrograms before feeding them to the convolutional layer. Ueki and Ara developed an MLP model to classify boiling regimes directly using sound pressure levels from a hydrophone with different levels of added noise [28]. They found that the heater surface shape impacts the acoustic signals and that it is possible to extract features representing the transition state from boiling sound frequencies. Although the integration of acoustic sensing and machine learning has led to encouraging progress in boiling studies, its implementation is still limited to qualitative analysis. To the best of the authors' knowledge, quantitative predictions of heat flux during boiling have been not demonstrated using acoustic sensing, owing to measurement noises and a lack of understanding of the relationship between thermal and acoustic signals.

In this paper, we have developed a machine learning framework for real-time heat flux quantification using acoustic signals. This framework combines acoustic sequence sampling with two feature extraction algorithms and three regressors to generate six machine learning models for boiling heat flux quantification. These models are trained and tested on acoustic signals captured using a hydrophone immersed in a boiling pool. The prediction accuracy and computational time of these models are compared. A subsequent parametric study is performed to examine the effect of the sequence length and sampling rate on the prediction accuracy. In addition, we have analyzed the differences in the acoustic signals in boiling regimes before and after CHF under the same heat flux.

Section snippets

Pool boiling experiments

All the data used in training and testing were obtained from pool boiling tests of deionized water on a polished copper surface. As shown in Fig. 1, the experimental facility consists of a 1 cm by 1 cm copper block submerged in deionized water pre-heated to the saturation point. A hydrophone with a built-in preamplifier (High Tech HTI-96-Min) is submerged in the liquid pool near the copper block and is connected to an NI DAQ system (chassis: cDAQ-9178; module: NI 9230) for data acquisition.…

Comparison of quantification error and computational time

The six heat flux prediction models under the developed framework are tested on a set of DS-1 data unseen during training in Fig. 5. Fig. 5**a, 5b, and 5c** represent the testing results of FFT-MLP, FFT-RFR, FFT-GPR models, and Fig. 5**d, 5e, and 5f** represent CNN-MLP, CNN-RFR, and CNN-GPR models. The blue and orange data points represent data in the nucleate boiling and transition boiling regimes, respectively. Ideally, every predicted point would equal the true point such that the data would all lie …

Conclusion

A machine learning model framework is developed for boiling heat flux quantification using acoustic signals. This framework explores and compares six model architectures generated from a combination of two different feature extraction methods (i.e., FFT and CNN) and three different regressors (i.e., MLP, RFR, and GPR). It was found that FFT-GPR and CNN-RFR yield the highest performance with MAPE much lower and R^2 scores higher than other models. Despite similar prediction accuracy, FFT-GPR has…

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.…

Acknowledgments

This work was supported by Arkansas EPSCoR Data Analytics that are Robust & Trusted (DART) seed grant number 22-EPS4-0028 under National Science Foundation grant number OIA-1946391, and the University of Arkansas Chancellor's Fund for Commercialization. This work used the Extreme Science and Engineering Discovery Environment (XSEDE) Bridges2 GPU at PSC through allocation TG-MCH200010, supported by National Science Foundation grant number ACI-1548562.…

Recommended articles

References (50)

C. Roe *et al.*
Immersion cooling for lithium-ion batteries – A review
J Power Sources (2022)

Q. Zhang *et al.*

[A survey on data center cooling systems: Technology, power consumption modeling and control strategy optimization]
Journal of Systems Architecture (2021)

J.P. McHale *et al.*
Nucleate boiling from smooth and rough surfaces - Part 1: Fabrication and characterization of an optically transparent heater-sensor substrate with controlled surface roughness
Exp Therm Fluid Sci (2013)

J.P. McHale *et al.*
Nucleate boiling from smooth and rough surfaces - Part 2: Analysis of surface roughness effects on nucleate boiling
Exp Therm Fluid Sci (2013)

G.M. Hobold *et al.*
Machine learning classification of boiling regimes with low speed, direct and indirect visualization
Int J Heat Mass Transf (2018)

S.M. Rassoulinejad-Mousavi *et al.*
Deep learning strategies for critical heat flux detection in pool boiling
Appl Therm Eng (2021)

A. Rokoni *et al.*
Learning new physical descriptors from reduced-order analysis of bubble dynamics in boiling heat transfer
Int J Heat Mass Transf (2022)

G.M. Hobold *et al.*
Visualization-based nucleate boiling heat flux quantification using machine learning
Int J Heat Mass Transf (2019)

T. Alhashan *et al.*
Identifying bubble occurrence during pool boiling employing acoustic emission technique
Applied Acoustics (Mar. 2018)

S.H. Baek *et al.*
Acoustic emission monitoring of water boiling on fuel cladding surface at 1 bar and 130 bar
Measurement (Oct. 2017)

View more references

Cited by (9)

A novel non-destructive acoustic approach for investigating pool boiling phenomena

2024, International Journal of Heat and Mass Transfer

Show abstract

Performance prediction of gas turbine blade with multi-source random factors using active learning-based neural network

2024, Applied Thermal Engineering

Show abstract

Acoustic sensing for investigating critical heat flux enhancement during pool boiling on electrodeposited copper foams

2024, Applied Thermal Engineering

Show abstract

Acoustic state detection of microbubble emission boiling using a deep neural network based on cepstrum analysis

2023, International Journal of Multiphase Flow

Show abstract

An intelligent strategy for phase change heat and mass transfer: Application of machine learning

2023, Advances in Heat Transfer

Show abstract

A Novel Non-Destructive Acoustic Approach for Investigating Pool Boiling Phenomena

2023, SSRN

View all citing articles on Scopus

View full text