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RESEARCH ARTICLE

Deep Learning-Based Predictive Modeling for Thermal-Aware and Reliability-Optimized VLSI System Design

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ABSTRACT

As the chips continuously advance in complexity and principle of tightly integrating into the VLSI channels, the thermal mechanism and dependability issue is among design considerations that are strongly sought after. The hotspots are due to high heat levels in localised areas and these processes result in imperfection in the system as well as electromigration and temperature change caused by bias and ultimately shortens the life of the system. In the thermal and reliability modelling practises that have been established, they typically involve physics-based modelling effort-consuming computationally with very little flexibility in adapting to dynamic design situations. In this article, a predictive modelling scheme of thermal-conscious and reliability-optimal design of VLSI systems is proposed on the basis of deep lefarning. High accuracy of a prediction of temperature distribution, high reliability at the initial design phases is the aim in order to optimise it in advance. It applies a hybrid deep learning model, which applies Convolutional Neural Networks (CNN) to derive Montage features and Long Short-Term Memory (LSTM) to derive temporal relationships. This is training of the model using the benchmark data sets that were created in the simulation environments that included power density, voltage and layout parameters. The experimental evidence suggests that the proposed method is characterised by high predictive performance and low root mean square error of thermal prediction is cheaper in nature than the conventional methods. In addition to it, the framework improves the metrics of reliability because it will be able to detect thermal hotspots in the initial phases due to the increased mean time to failure (MTTF). The proposed solution presents a good and scalable solution to the introduction of AI-based predictive analysis into VLSI design cycles which will be useful to thermal control and long-term reliability.

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INTRODUCTION

The ability to increase the level of computational performance and spatial density, which is continuously growing, has become achievable because of Very Large-Scale Integration (VLSI) systems. However, as the transistor size has reduced and the degree of integration has increased, the power density has increased enormously and currently, it is the thermal issues of low-level chip designs which are problematic. Hotspots also occur in the locality of high temperatures and distorted heat circulation that adversely affect the performance of any given system besides improving the processes of degradation of different devices. It has therefore been observed that thermal management is among the most important needs in ensuring reliability and long lifetime of the VLSI systems.[4, 7]

Thermal effects in high VLSI systems have been established to be closely related with issues of reliability. A higher operating temperature enhances modes of failure which involve electromigration (EM), bias temperature instability (BTI) and time-dependent dielectric breakdown (TDDB). These effects increase the mean time to failure (MTTF) by a huge margin as well as impact the overall system robustness. Previous research has taken into consideration routing thermal-sensitive and adaptive network-on-chip (NoC) architectures because of the importance of considering the issues of thermal and reliability during the design stage.[3–5]

The traditional techniques of thermal and reliability modelling are largely physics-based techniques and are founded on finer details of simulation. Even though they are correct, these strategies are computationally expensive and even too small and complex VLSI systems. Besides, they are not conducive to dynamic and real-time design optimization and thus are not related to modern Electronic Design Automation (EDA) procedures.

The recent technological advancement in the sphere of Artificial Intelligence (AI) and, particularly, deep learning has created a significant prospect of addressing these challenges. Data-driven models can be effective in learning complicated nonlinear designs where responses to design parameters can be correctly and efficiently predicted using the generated models. The techniques applied successfully in predictive modelling tasks in any engineering field where they have been applied include neural networks and hybrid learning models which have been performing better than the conventional methods [2], [9]. Despite this progress, research on how to optimise thermal and reliability consideration together through the assistance of deep learning in VLSI systems has less literature.

This paper addresses the deficiencies by designing a deep learning-based predictive modelling system of thermal conscious and reliability-constrained design of VLSI systems. The method proposed follows the hybrid model based on which both time and space information as to the alterations of the temperature can be also secured in order to predict it and then optimise it on the first sketch of the design.

Key Contributions

The major contributions of the work are the following ones:

- Deep Learning-Based Predictive Model: A hybrid deep-based learning model is developed in order to determine the temperature pattern and reliability measure of the VLSI systems effectively.
- Thermal and Reliability Co-Optimization: The proposed approach is a combination of thermal sensitive analysis and reliability analysis that will overall improve the system lifetime.
- Enhanced Design Efficiency: The structure enables ahead of time anticipation and optimisation by diminishing the utilisation of computationally intense simulation.
- Treatment Healing velocity: what varies most: The model is much more precise than the conventional modelling methods, which makes it able to be employed in designing.

RELATED WORK

Thermal modelling has emerged as one of the primary topics under discussion in the VLSI system design since the emerging integrated circuits are becoming increasingly dense in terms of power. The traditional approaches of thermal modelling have a tendency of employing physics based models to represent temperature distributions in the form of thermal chips as finite element and compact thermal models. In various studies regarding Network-on- Chip(NoC) applications, thermal-conscious routing algorithms have been put forward to avoid hotspots and maximise the amount of heat removed. An illustration is the adaptive routing techniques that are invented to provide dynamically assigned traffic and localized thermal stress minimization of 3D NoC systems.[3, 4] Further developments and utilisation of the earlier approaches have extended it to apply traffic and thermal awareness in enhancing the system stability further.[5] Moreover, now proposals of mobile thermal management systems have been put forward to cheque and monitor variations with temperature in playtime.[7]

The clever estimate of trustworthiness in VLSI systems borders closely with the thermostatic effects, as well as the weakening of long term factorization procedures. The conventional methods are premised on the formulation of analytical and empirical equations of conventional failure mechanisms such as the electromigration (EM), bias temperature instability (BTI), and time-dependent dielectric breakdown (TDDB). They are described as being intensive in terms of simulations and prepared models, being computationally intensive and less adaptable to the altering circumstances of designs. Other indirect means have also been explored including architectural solutions, e.g. noC designs with low power usage, optimal packet routing, as a way of enhancing reliability by reducing thermal stress.[6, 10]

With the idea of VLSI systems becoming even more difficult, the process of Artificial Intelligence (AI) and Machine Learning (ML) has come into the limelight because of their ability to explain nonlinear relations, as well as conduct data-prelined optimization. Reducing dimensionality techniques and feature extractions techniques that have been utilised in modelling tasks include principal component analysis (PCA).[1] In addition, adaptive neuro-fuzzy inference systems and Hybrid metaheuristic models have also been proven to be useful in predictive modelling of complex engineering parameters.[2] It has also been found that data-based approaches to similar areas have improved better system optimization and more accurate prediction.[9]

In the past few years, deep learning is an effective tool of Electronic Design Automation (EDA) and offers superior prediction capabilities, optimization, and decision-making. Architectures Neural network and neural network models have been explored in performance estimation and power prediction, in exploring design space. Those methods are more inference as well as scaled as compared to the conventional inference methods of simulation. However, most deployed deep learning in the VLSI system are focused on individual variables such as power, performance, and minimal endeavours have been made on integrated thermal and reliability reporting.

Research Gap

Despite all the work done in the area of thermal-conscious design, reliability modelling and AI-based optimization, several questions remain unanswered:

- Lack of Integrated Thermal and Reliability Prediction Personnel: In the literature, all the current studies concentrate on thermal management and reliability estimation as individual challenges, and do not have a unified paradigm of prediction.
- Limited Deep Learning-based Joint Optimization: In spite of AI/ML applications to VLSI, few efforts to apply deep learning to estimate joint thermal and reliability have been done.
- Scalability and Computational Constraints: The techniques of playback simulation that were popularly used in the past are computationally complex and cannot be optimised with a large scale or real-time design.
- Lack of Prediction Accuracy in Complex California Pizza: In the current VLSI systems most of the available models do not perform well in realising complex spatial and temporal dependence and therefore poor predictions.

METHODOLOGY

System Overview

The system being suggested presents an introduction of a deep learning-powered predictive system that can allow thermal-aware and reliability-aware VLSI system design. The overall structure will embrace the data-driven modelling and design parameter analysis to get valid predictive values in the determination of temperature distribution and values of reliability into lower levels of design flow. It is not heavily dependent on computationally expensive simulations and it can be applied in Electronic Design Automation (EDA) to assist in the making of efficient decisions.

The framework operates under the consideration of multiple design related inputs which are: power density,

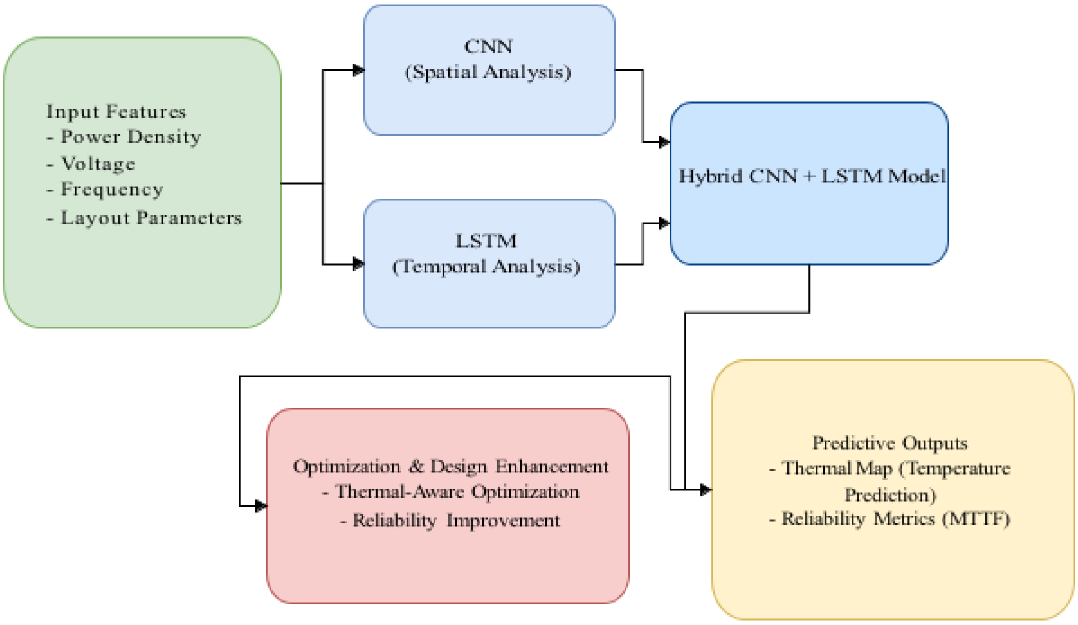

Fig. 1: Proposed Deep Learning-Based Thermal and Reliability Prediction Framework

supply voltage, operating frequency and layout specific parameters. All these attributes are normalised and scheme of feature scaling are preprocessed so as to provide uniformity and improve convergence of the model. The subsequent processed information is then passed into a hybrid deep learning architecture consisting of the Convolutional Neural Networks (CNNs) to learn spatial relations in layout and thermal patterns and the Long Short-Term Memory (LSTM) network to learn temporal relations in workload and dynamic response.

The results of the deep learning algorithm in the shape of predictive temperature distributions maps and mean time to failure (MTTF) reliability measurements. They also apply the predictions in optimization that is thermal conscious as well as reliability that the designers can get to know of the areas to be hotspots and likely to cause failures at a very early stage. The efficacy and extent of the design is improved by the thermal and reliability consideration in a unanimous predictive structure, as proposed in the proposed system.

The overall workflow of the proposed framework is illustrated in Figure 1, highlighting the flow f0rom input feature extraction to predictive outputs and optimization.

Data Collection and Preprocessing

As it is, the accuracy of the proposed deep learning-based predictive system highly depends on the quality and the diversity of the dataset provided to train and test the system. This work produces data by use of simulation-based environments and standard benchmark circuits that are commonly utilised in the VLSI design research. Network-on-Chip (NoC) architectures such as Network-on-Chip and synthetic workloads are measured on benchmark suites to find realistic variations on power consumption, thermal distribution and behaviour. They are based on these datasets so that the model is exposed to different design circumstances that improve its generalisation capability.

It is a collection of different characteristics of input, given direct impact on thermal behavioural properties and reliability properties of VLSI systems. These features include power density which determines how much heat different components of the chip give off, supply voltage which determines both the power consumption and device stress and operating frequency which determines the switching activity and dynamic power. The layout choices, the position of components, the structure of interconnections among them are also introduced to represent the spatial dependencies and pattern of development of hotspots. All this enables the model to characterise sophisticated models of connexions between design values and thermal-reliability outcomes.

The obtained data go through pre-processing steps like normalisation and scaling to enhance the working of the model and ensure that the model remains stable during the training process. The all-input variables are scaled to normalised range by the utilisation of Min-max scaling to further improve convergence of the deep learning model. This is followed by partitioning a dataset into training, validation and testing whose fraction is normally 70:15:15 to test the build generalisation of the model and overfitting.

Table 1 gives a summary of the dataset features and description of the features.0

Deep Learning Model Architecture

The proposed framework structure will be based on a hybrid deep learning structure that will effectively model both spatial and time varying behaviour of current in VLSI systems using both the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network types of models in parallel so that advantages of both models can be combined. The CNN component identifies spatial characteristics of layout-sensitive inputs such as power density maps and structural parameters and the LSTM component identifies any temporal dependence that manifests itself because of the changing operating conditions such as workload variations and frequency variations. Temperature distributions and measures of reliability are better predicted under this mixed method.

The CNN block co0nsists of few convolutional blocks and followed by pooling blocks to reduce the dimensions and high-level spatial details. To introduce non-linearity to increase the learning efficiency, one uses rectified line

Table 1: Dataset Features and Description

Feature	Description	Impact on System
Power Density	Distribution of power consumption across chip regions	Directly influences heat generation
Voltage	Supply voltage applied to circuit components	Affects power consumption and reliability
Frequency	Operating frequency of the system	Determines switching activity and heat
Layout Parameters	Physical placement and interconnect structure of components	Influences spatial thermal distribution

units which are also known as ReLU. The resulting feature maps are then flattened and the output sent to the LSTM network which includes one or more recurrent layers to develop sequential Dependencies. The LSTM layers utilise the gating mechanism so that the vital information over time could be recalled and the issue of the vanishing gradient could be addressed.

A densely connected (full) layer is the final output layer that is used to provide out predictions of thermal maps and reliability measure such as mean time to failure (MTTF). The continuous basis is facilitated by the presence of a linear activation function at the output layer in order to be able to predict the values more easily.

During training, the model uses as the loss function the Mean Squared Error (MSE) to minimise the error of prediction. The reason behind the use of Adam optimizer is that it possesses adaptive learning rate characteristics and is highly convergent. Other training parameters include: batch size, learning rate, and epochs; which have been experimentally assigned in order to achieve optimum performance and generalisation.

The detailed architecture of the proposed hybrid CNN-LSTM is presented in Figure 2 that demonstrates thus the data flow in the convolutional, recurrent, and fully connected layers shape.

Thermal Prediction Module (Updated with Figure Explanation)

The thermal prediction module is a significant component of the framework suggested as well and will be created on the premise that it is rightfully aligned to the distribution of temperature and identify the potential hotspots within the VLSI systems. High levels of heat generation and non-uniform heat distribution, as it is mentioned in the abstract, are great contributors to system performance and quality. The above therefore implies that there is a necessity of more efficient predictive mechanism to streamline design at an early stage at thermal-conscious design.

In the proposed approach, hotspots of temperature prediction has been performed by use of hybrid CNN-LSTM model. The CNN term removes the spatiality of input images in that they contain power density maps, layout parameters and they may result in the model acquiring knowledge about localised patterns of heat distribution across the chip. These space features are vital in identifying spaces where the capability of concentration of power is intense that are likely to experience a thermal hot spot.

File LSTM network takes the extracted features representations to receive the alterations of time with changing operating conditions including the changes of workloads behaviour and frequency. This makes this model take into account dynamical changes in temperature over time that improves the accuracy of estimation of hotspots within the existing variables of operation.

The model generates a successive thermal map of the approximate temperature field at different locations of the VLSI system. Identification of hotspots is by with the help of an analysis up to a given threshold over which areas which exceed a specific temperature level are considered to be critical zones. That will enable determining the existence of thermal risks in time and even actively adjust the design.

As Figure 3 illustrates, the thermal-conscious circuit layout is a representation of multiple functional objects of the CPU core, memory, I/O, power module, and logic unit that are put on the chip. The overlapping heatmap indicates places that have high heating temperatures and the red and orange spots are thermal hotspots, when compared to the colder places that are denoted by the blue and green colours. Such hotspots are typically

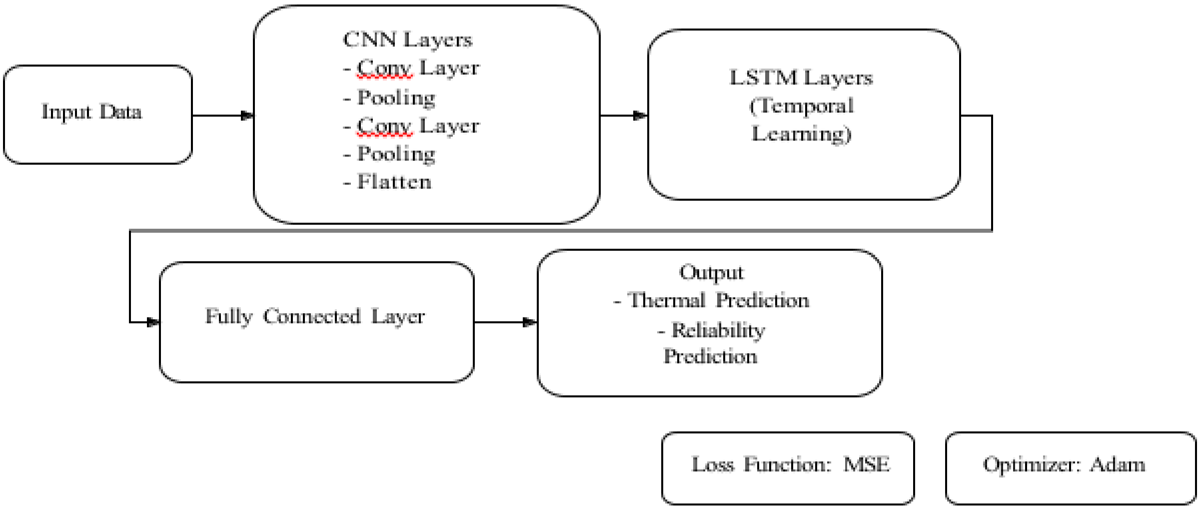

Fig. 2: Hybrid CNN-LSTM Deep Learning Model Architecture

located close to the high-power content components such as the processing cores and the power modules. The visualisation demonstrates that the model is useful in effective prediction of critical thermal regions in the model based on the spatial temperature variations that are obtained by the model.

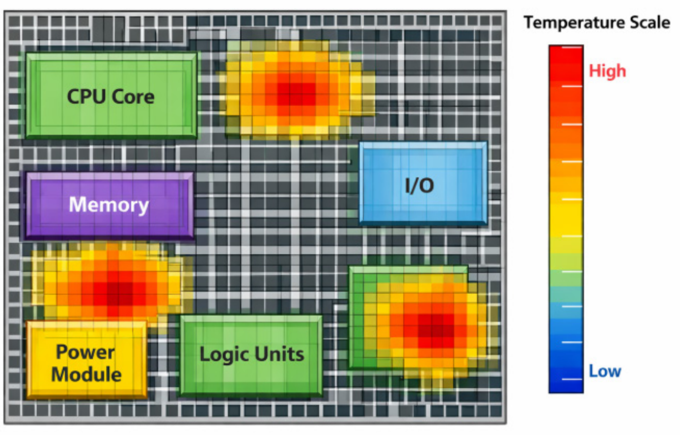

Fig. 3: Thermal-Aware Circuit Layout with Hotspots

The proposed thermal prediction module is a scalable and faster in prediction than the conventional simulation-based methods due to the utilisation of deep learning to spatially and temporally process the received information. This prevents real-time optimization of thermal sensitivity and global efficacy and dependability of system design of VLSI.

Reliability Modelling (Added Figure Explanation)

The proposed framework also needs reliability modelling that will assist in modelling the major thermal effects of the systems as the performance and the lifespan of the VLSI systems are the only parameters that directly relate to the thermal effects as well. The high temperature, hot zones, augment the pace of equipment degeneration mechanisms as it is mentioned in the abstract, and thus, reliability estimation and thermal forecasting should be integrated. The proposed solution is based on the outcomes of the deep learning assisted thermal model to consider the most crucial reliability indicators and perform proactive design optimization.

The primary measure of reliability that will be considered in this paper is Mean Time To Failure (MTTF) and it is the expected time that a device will operate to its failure. Pinpointing of MTTF is donated to use of the predicted temperature records in which, high temperatures are likely to cause exponent growth in terms of dependability of the devices. Temperature-dependent reliability models are employed in the framework to provide the accurate lifetime predictions of different portions of the chip.

In addition to the MTTF, the model also considers Electromigration (EM), which is a significant assumption of failure, which ensues due to the slow passage of metal atoms in interconnects, as a consequence of the large volume of current density and high-temperature. The proposed system evaluates the EM effects by evaluating it on the premise of comparing the predicted thermal hotspots with the current density variations demonstrating the most susceptible points to interconnect failures.

Another quite important factor that is taken into account is Bias Temperatures Instability (BTI) as the threshold voltage of transistor varies over time, provided that the temperature is raised substantially as well as due to the electrical stress. The structure uses the BTI-affinity analysis by reference to a connexion of the forecast of the temperature with the ageing characteristics of the device

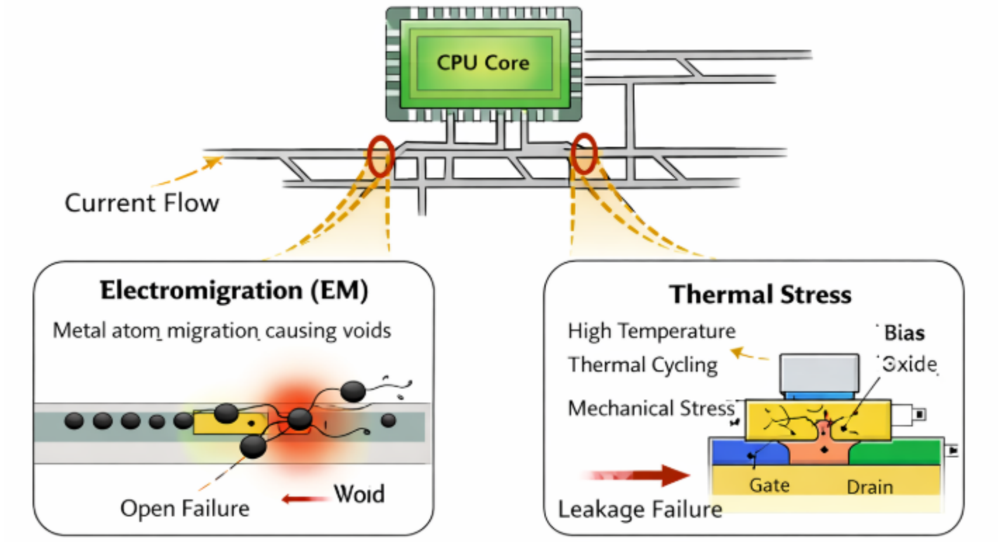

Fig. 4: Reliability-Aware Circuit (Electromigration Effect)

which permits forecasting the performance drop more graphically.

A circuit diagram sensitive to reliability such as in Figure 4 would indicate the significant level of degradation to VLSI systems. The flow of current using metal interconnects has been depicted in the diagram and in electromigration, holes are left, resulting in an open-circuit failure. This is particularly prone in areas that have large current densities and temperature. It also depicts thermal, as well as stress on transistorizing like a degradation of gate oxide because of BTI. The consequences of these effects are leakage current and degradation of time. This is clearly depicted by the visualisation that reliability degradation of integrated circuits is realised by a mix of thermal hotspots and electric stress.

Also, in the case of these reliability measures as well as predicting the thermal phenomenon of deep learning, the suggested model provides a comprehensive assessment of reliability. The coupled approach allows the designers to identify the risk areas early in the design process and to embrace the mitigation procedures such that in the end the system resilience and the life time operation of the VLSI systems has been increased.

Optimization Strategy

The strategy to achieve optimization included in the proposed framework involves the application of predictive capabilities of the deep learning model to optimise design decisions on thermal management and reliability. In the abstract, patient optimality, early detection and feasibility subsumes the fact that proper early prediction of temperature distributions and reliable parameter results in proactive optimization and cheaper outcomes of a sequence of post-design changes and computerised simulations.

The thermal map estimates and the reliability indicators are highly significant inputs, which are factored in estimating the ways of making design improvements. The developers do not have to guess both during flooring time, placement and routing time, which is made possible using the hotspots and high-risk area. One instance is the strategic relocation of the high-power-density components with reduced concentration whereby heat is difficult to form a hot spot thereby resulting in improved heat loss over the chip. Similarly, it is possible to modify the routing tracks to balance out the flow and to alleviate overloading in certain spots.

In addition to optimization of the structure, the framework enables the dynamic voltage scaling (DVS) as an appropriate tool to promote the benefits of thermal and reliability. The possibility to manage the power resource by adjusting the supply voltage according the predicted thermal conditions and limit the rise of temperature without significant alteration of the performance can assist the system to conserve power and reduce the temperature. Operating voltages are also reduced thereby inhibiting degrading mechanisms that may be caused by stress, which considerably results in improved device lifetime.

A combination of thermal aware placement and routing optimization and voltage scaling to a single predictive model allow such a design approach to be holistic. Unlike the conventional methods where the adjustments are responsive, the provided strategy will enable simplifying the process in a more proactive and more data-oriented way that will ensure a better thermal balance and the enhancement of reliability. The net result of this is design efficiency, low failure rates, and long life in VLSI systems of today.

EXPERIMENTAL SETUP

The efficacy of the proposed design of thermal-conscious and reliability-grade VLSI system, which is based on deep learning, will be measured using the experimental model. According to the abstract, this is done to determine the accuracy, the efficiency, and scalability of the model in estimating the temperature distribution of the model, and the reliability measures.

To develop and train the given model, the proposed model is implemented in Python and deep learning frameworks such as TensorFlow/Keras or PyTorch. The production of simulation data based on realistic power, thermal, and layout simulation is done with the Electronic Design Automation (EDA) software that operates on Cadence, and Synopsys. Also, it is possible to use MATLAB in order to preprocess and validate the results.

Fast Tests have been exercised on a multichip processor machine, with enough random-access memory (e.g. 16 GB or larger) and optional graphics card acceleration in order to hasten training and inference. The software environment is its set of standard libraries of scientific computing to manipulate, visualise and conduct performance analysis.

The model is then trained and tested on a collection of well-known popular circuit boards such as ISCAS and ITC suites and on synthetic workloads to make it robust and be capable of generalisation. These situations propose a large variety of design situations with non-similar power consumption history and structural compoundness and, accordingly, permit a full evaluation of the proposed strategy.

The model performance is measured using different measures. Conventionally, the closest accuracy in a thermal prediction is to involve a combination of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) that are used in making predictions and actuals of temperature. The improvement in reliability is revised as percent change of certain of the measures like Mean Time to Failure (MTTF). In addition, the runtime analysis is used to determine the amount of the computational performance when the proposed solution is compared to the classical methods of the suggested solution, which are based on the analysis through simulations.

The entire experiment that includes generating the data, preprocessing, model training as well as evaluation which provides a clear picture of how it was done.

Thermal Performance based on prediction.

The developed hybrid CNN-LSTM will be tested on the basis of the competence to predict the temperature of VLSI systems. To measure the performance, root mean square error (RMSE) and Mean Absolute error (MAE) are employed. The signal signal model will yield significantly lower prediction error than traditional physics-based models since it expresses nonlinear spatial and time dependence.

The result values of the prediction as shown in Figure 5 are rather close to the properties of thermal profiles and this is a good sign of accuracy and consistency. The model is appropriate in determining the locations of the hotspots with confidence that the thermal control is going to be taken in the design phase.

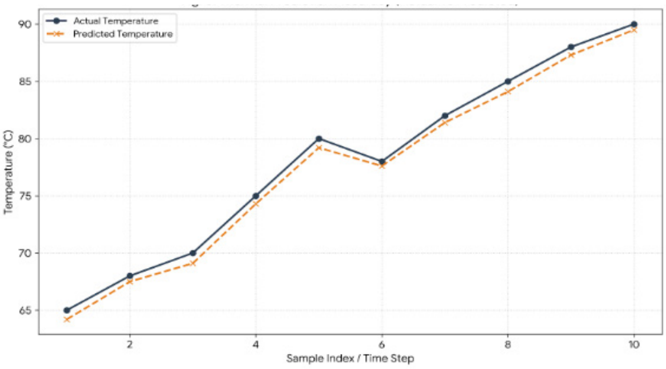

Fig. 5: Thermal Prediction Accuracy (Actual vs Predicted Temperature)

Reliability Improvement

The suggested frame would contribute to the improvement of reliability of the system because it would identify thermally critical areas at the initial stage. Jurisdictional of predictive thermal analysis in combination with the model of reliability, the framework reduces the jeopardy of the occurrence of the mechanisms of the failure, such as the electromigration and thermal stress.

Figure 6 shows the gains on the Mean Time of Failure (MTTF) of the mean gains above the baseline. The results demonstrate that the system lifetime has significantly risen proving the fact that the suggested approach is efficient in the validity of the reliability optimization.

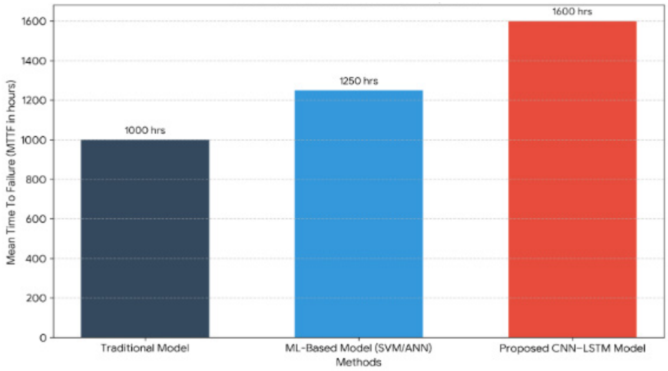

Fig. 6: Reliability Improvement (MTTF Comparison)

Comparative Analysis

Compared to more conventional methods of thermal modelling and existing machine learning methods, it is reviewed in Table 2. It has been determined that the offered model is better compared to the two categories with references to the precision and improvement in the aspects of prediction, and with efficiency of calculation.

Ablation Study

An ablation study is carried out to investigate the worth of all the elements in the frameworks proposed by investigating the variants of the models, including CNN-only, LSTM-only frameworks. The results indicate that CNN model is reasonable to capture the qualities of the spatial coefficient of the thermal distribution but fails to capture the time relation compared to LSTM which may be able to capture the time relation and fails to capture

Table 2: Performance Comparison with Existing Methods

Method	RMSE (°C)	MAE (°C)	MTTF Improvement (%)	Runtime Efficiency
Traditional Thermal Model	4.85	3.72	5%	Low
ML-Based Model (SVM/ANN)	3.12	2.45	12%	Moderate
Proposed CNN–LSTM Model	1.95	1.48	25%	High

the spatial relation inherent in the VLSI layout. On the other hand, the hybrid CNNLSTM model is the most ideal one since the model has the ability to combine the power of both spatial and time features. Additionally, feature level analysis shows that important inputs, such as power density and layout parameters, impact negatively on prediction accuracy to a significant extent and thus are significant in the accurate representation of thermal performance and reliability.

DISCUSSION

The key strengths of the proposed framework include high accuracy of prediction based on the hybrid CNN-LSTM architecture since there is the capability to predict the features of the thermal behaviour both spatially and in time. It provides a complete solution where thermal and reliability analysis will be performed all at once without the need to apply various modelling tools. It is also characterised by a high decrease in cost of computation that is even less than sight of virtual simulation based and can be generalised to complex VLSI systems. However, it also has certain flaws such as the quality and variety of training data usage which may influence the model performance as well as the increased time spent on the training at the initial steps in case of big datasets. In addition, actual silicon data is not significantly validated. However, it has been discovered that the framework is highly scaled and one can implement it to large scale VLSI designs and 3D integrated circuits. It has the potential to serve as an eventual solution to real-time design optimization and next-generation AI-directed chip design solutions because it can be integrated into the current EDA workflows.

FUTURE WORK

Despite the fact that it has already been demonstrated that the proposed deep learning-based framework experienced the growth of predictive thermal and reliability optimization on a massive scale, we can find several ways of enhancing the framework in the future. One such direction is the use of the model to real hardware systems, such as FPGA or ASIC systems, by which it would be possible to use thermal sensors on the chip and actively regulate it. This would allow an active optimization of the performance of the system under different loads and operating conditions.

Another possible extension, which potentially is rich in value, is likely the addition of the proposed framework with industry-standard Electronic Design Automation (EDA) tools. Through the explicit transformation of the design processes into the engine of AI-based predictive models, automated thermal-sensitive upkeep, routing, as well as power optimization of design processes to lower design degrees might be promoted to get rid of design cycles and design-to-market times.

Moreover, the use of the most recent deep learning structures is likely to offer the possibility of improving performance and scale. Circuit connectivity can be modelled using new architectures such as Graph Neural Networks (GNNs), and interdependences can be modelled in a more natural way, and transformer-based models are more able to reason observed long-range relationships and design patterns than classic models. The research of these techniques can be further implemented in enhancing the predictability and adaptability.

As a rule, the following work will be devoted to the issue of the integrated simulation and the actual world implementation, the better utilisation of the practical design tools, and the application of next-generation models of AI to create intelligent VLSI system design.

CONCLUSION

The current article presented an architecture of predictive framework design of VLSI thermal and reliability-optimised design with deep learning. The proposed solution relies on the hybrid CNNLSTM architecture, which has the ability to obtain both spatial and time characteristics of the thermal phenomenon and, thus, effectively predicts the distribution of the temperatures and metrics of reliability such as the mean time to failure (MTTF). The article is based on the combination of thermal analysis and the ability to estimate the reliability into one framework and addresses some of the biggest deficiencies of the classic simulation-based solutions.

As it can be observed by the experimental data, the suggested model is significantly superior to the existing and traditional models of machine learning in terms of accuracy when predicting, the efficiency of computation or the improvement of reliability. The framework has been in a position to trace heating hotspots and enable optimization of the systems in the initial phase and has led to a prolonged duration of system lifetime and a reduction in the failsures. Moreover, generalisation of benchmark circuits also is a sign of the power of the method.

In practise, the suggested framework offers an applicable and effective solution to the VLSI design issues that have become more recent. Its functionalities that it includes together with the Electronic Design Automation (EDA) workflows enable the designers to introduce the predictive intelligence into the design process that reduces the time of development and increases the performance of the system.

In conclusion, deep learning could be an effective and powerful tool when it comes to solving complex thermal and reliability problems in VLSI systems. The further automation of design with the assistance of AI provided in the suggested complex allows the opening of the way to the production of the more reliable, efficient, and intelligent semiconductor systems.

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