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Exploring the Role of Artificial Intelligence in Modern Analog Circuit Design

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Abstract: *In this review paper, various approaches to machine learning are being reviewed. This work is a review. In addition, significant aspects such as power efficiency, latency, and accuracy are being taken into consideration in order to verify the output. The flow of the paper begins with a fundamental introduction to machine learning and analog circuits, followed by a discussion of various machine learning techniques. Following that, the application of machine learning to analog circuits is discussed using a variety of methods, and finally, the conclusion and references are presented.*

Keywords: Analog-to-Digital Conversion, Signal Amplification, Filter Design.

I. INTRODUCTION

Although machine learning (ML) is one of the most popular and demanding buzzwords these days, there hasn't been much progress in integrating ML techniques into EDA tools, even though EDA deals with a lot of big-data concerns. Algorithm-related parameter selection and training for a number of EDA machine learning applications must take place entirely within the computer environment of a design client or industry.[1] A significant number of SoC parameters, such as floorplan, routing constraints, available resources, connectivity requirements, protocol level dependency, clock characteristics, process characteristics like wire delay, power budgets, bandwidth and latency constraints, etc., influence the ideal interconnect strategy. The design space becomes unnecessarily vast as the number of distinct dimensions inside the design strategies space increases to hundreds. EDA is typically where machine learning is used.

We will forecast the effects of bugs, design complexity, human resources, licenses, and compute farm throughput on ongoing projects by examining billions of knowledge points from prior outputs. We can provide forward prediction and detect any delays by locating bottlenecks in semiconductor designs. With the use of sophisticated algorithms already in place, machine learning can be leveraged to reduce the time required for simulation and design. [5] Out of millions of potential solutions, machine learning techniques are prepared to evaluate previous compilation outcomes and forecast the best synthesis/place-and-route parameters and placement sites. [3] They use statistical modeling and machine learning to determine the optimal tool parameters for a design, extracting insights from the data to improve the caliber of outcomes. In EDA, machine learning has already started to take a significant role.

II. MACHINE LEARNING TECHNIQUIES

These days, there are a lot of misconceptions surrounding the terms artificial intelligence (AI), deep mastering, and device gaining knowledge of. Most people assume that these terms are interchangeable, and when they hear the term AI, they immediately associate it with device gaining knowledge of or vice versa. Machine learning is the process of analyzing statistics, drawing conclusions from them, and using those conclusions to make informed decisions. The main difference between deep and machine learning is that while gadget learning models become better with time, they still require some coaching. In the case of deep mastering, the version handles it on its own, but if a system mastering model yields a flawed prediction, the programmer must actively fix the issue. One excellent illustration of deep learning is the automatic car driving system. "AI is the ability of a computer program to function similarly to the human brain." AI can be achieved by machine learning and deep learning, which implies that while AI isn't always possible, we may eventually be able to obtain it through the application of these techniques.

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There are several distinct approaches and a large number of algorithms. Regression, classification, clustering, association, dimension reduction, anomaly detection, data mining, and recommendation systems are a few of the methods.

Table 1: Difference of Al, Ml and Dl

Artificial Intelligence	ML	Revolution of ML
Computer vision	Classification	Deep learning
Lang processing	Clustering	
creativity	Neutral network	

In addition to various methods, there are various algorithms, such as supervised and unsupervised.

A. Supervised algorithm:

It is employed to monitor and guide the completion of a task, project, or activity. Teaching the model is how it is accomplished. Thus, we teach the labeled dataset and load the model based on knowledge. Additionally, the features that contain the data indicate COLUMN, and the attributes will indicate ROWS. In essence, there are two categories of data: numerical and character or category. Regression and classification are the two techniques that are used in supervised learning. Predicting distinct class labels or categories is the process of classification. The process of forecasting continuous values is called regression.

B. Unsupervised algorithm:

Allowing the model to work on its own and uncover facts that may not be visible to the human eye is preferable to providing supervision. It's the challenging algorithms. Several methods, such as dimension reduction, market basket analysis, clustering, and density estimation, which is utilized to identify some structure within it. In contrast, clustering is the process of identifying a set of data points or objects that are somewhat similar through the use of summarization, anomaly detection, and structure discovery.

Table 2: Supervised V/S Unsupervised

Supervised	Unsupervised
Classification Deals with labeled data	Clustering Finds patterns and grouping from unlabeled data
Regression Predicts trends using previous labeled data	
Has more evaluation methods	Has fewer evaluation methods than supervised learning
Controlled environment	Less controlled environment

III. REGRESSION TECHNIQUE

A. Simple linear Regression

In addition to describing the relationship between two or more variables, it is used to predict continuous values using other variables. There are two variables in basic linear regression: the dependent and the independent. The dependent value should be continuous rather than discrete, while the independent variables can be assessed using a continuous or categorical scale.

Topology: When estimating a single dependent variable from a single independent variable, simple linear regression is employed.

Working:

$$Y=\Theta_o+\Theta_1X_1$$

The dependent variable is Y. The independent variable is X1.

The parameters that need to be changed are o and 1.

The slope is denoted by 1, and the intersect by o.

Another name for o and 1 is the linear equation's coefficient. The coefficient of line is estimated via linear regression. To determine which line best fits the data, o and 1 must be computed. Error should be minimized in order to modify the parameters so that the line fits the data the best.

$$MSE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - y)^2$$

There are two approaches:
1) Mathematical approach
2) Optimization approach.

Mathematical approach:

$$\Theta 1 = \frac{\sum_{i=-1}^{S}(xi-xb)(yi-yb)}{\sum_{i=1}^{S}(xi-xb)^2}$$

Where, X_b= mean of independent value and Y_b= mean of dependent value and $\Theta_o = y_b - \Theta_1 * x_b$.

B. Pros of Linear Regression:

Vary Fast
No parameter tuning
Easy to understand and highly interpretable
Model evaluation: The two fundamental methods are Train/Test Split and Train/Test on the same dataset.

C. Train and test on the same dataset:

$$Error = \frac{1}{n}\sum_{j=1}^{n}|yj - jy(cap)|.$$

Where y(cap) is the projected value and y is the actual value. This method has low out-of-sample accuracy and good training accuracy.

The percentage of accurate predictions the model makes using the test data set is known as training accuracy. High training accuracy isn't always a good thing, though. Additionally, over-fitting when a model is too closely trained to a dataset may lead to noise capture and a non generalized model.

The percentage of accurate predictions the model generates on data that hasn't been used for training is known as out-of-sample accuracy. The model's high out-of-sample accuracy is crucial, hence there are methods to make it better: Train/test split, another evolution strategy, is one method.

Splitting the data set into training and testing sets, which are mutually exclusive, is known as the "train/test split." Because the testing dataset is separate from the dataset used for data training, it offers a more accurate assessment of out-of-sample accuracy. The problem is that the datasets used for training and testing are very dependent on each other. Another method known as K-fold cross validation fixes the majority of the problems.

Cross-validation using K-fold: In this case, k is the amount collected in order to verify the data. The first 25% of the data is used for checking if k = 4 fold. and take a break for training. The second 25% is then taken in the following fold, and this process continues for all folds. Considering that no data is replicated, the outcome is average. In its most basic version, k-fold cross-validation conducts several train/test splits. The average is the result of using the same data set in different ways for each set.

Regression evaluation measures are used to describe a model's performance. It plays a crucial part in the creation of a model since it highlights areas that need work.

ERROR: discrepancy between the algorithm-generated trend lines and data points

MAE (Mean absolute error) = $\frac{1}{n}\sum_{j=1}^{n}|yj - jy(cap)|$

This is the easiest of the metrics to understand.
Since it is just an average error

MSE (Mean square error)= $\frac{1}{n}\sum_{j=1}^{n}(yj - jy(cap)\ \hat{}\ 2)$.

RMSE (Root Mean Square Error) = $\sqrt{\frac{1}{n}\sum_{j=1}^{n}(yj - jy(cap)\ \hat{}\ 2)}$.

This is one of the most popular.

RAE (Relative absolute error)= $\frac{\sum_{i=-1}^{s}|yj-yj(cap)|}{\sum_{i=1}^{s}|yj-yb|}$.

RSE (Relative square error) = $\frac{\sum_{i=-1}^{s}(yj-yj(cap))\hat{}2}{\sum_{i=1}^{s}(yj-yb)\hat{}2}$.

It is used to calculated R2 = 1- RSE.

The higher the R2 the better the model fits the data.

D. Multiple Linear Regression

It is a development of the basic linear regression model. These are the applications:

1) Effectiveness of independent factors on prediction: If we want to determine how strongly the independent variables influence the dependent variables.

2) Predicting the effects of changes: Understanding how the dependent variable changes when the independent variable is changed is one way to predict the effects of changes.

It's a technique for forecasting continuous values. Examining which variables significantly predict the outcome variable is a highly helpful application of it.

$Y(cap) = \Theta_0 + \Theta_1\, x1 + \Theta_2\, x2 + \ldots + \Theta_n\, x_n.$

So, $y(cap) = \Theta^T.X$

x is the independent value and feature set, y is the dependent value, and is the parameters. We have to reduce the mistake in order to accomplish this. We must comprehend the optimal parameters and the process in order to determine them. The model with the fewest errors is the result of optimized parameters. There are methods for estimating that are called:

1. Ordinary Least Squares minimizes the MSE in an attempt to estimate the value of the coefficient. It makes use of linear algebra, but for large datasets (10k+ rows), it takes a lengthy time.

2. Optimization algorithm: you can use an iterative approach to minimize the model's error on your training data in order to optimize the value of the coefficient and determine the optimal parameters.

Similar to gradient descent, this method works well with huge datasets.

E. Non-linear regression

It is a technique for simulating a non-linear relationship between a group of independent factors and the dependent variable. A model must be non-linear as a function of the parameters ̧ not necessarily the features x, in order for y to be deemed non-linear. It can take many different forms, including logistic, logarithmic, and exponential shapes. In other words, the model is nonlinear by parameters in non-linear regression. Ordinary least squares techniques cannot be used to fit the data in non-linear regression, in contrast to the linear regression method. Because estimating parameters is difficult.

F. Introduction to classification

Aims to discover a relationship between a collection of featured variables and a target variable of interest by classifying certain unknown items into a discrete set of categories or classes. This method is known as supervised learning. Discrete values of a categorical variable are the target attribute in a classification. For an unlabeled test case, classification establishes the class label. Applications for classification include document classification, biometric identification, speech recognition, email filtering, and much more.

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Classification algorithms in ML
Decision trees (ID3, C4.5, C5.0)
Naïve Bayes
Linear discriminant analysis
K-nearest neighbor
Logistic regression
Neutral networks
Support vector machines (SVM).

IV. MACHINE LEARNING IN ANALOG DESIGN

Using machine learning to optimize mixed-signal designs quickly and accurately [1]: To reflect the very non-linear nature of analog blocks, a machine learning model known as the Artificial Neural Network Meta-model (ANNM) has been investigated. Here, OP_AMP and PLL are being built, and an OP_AMP design in the i_{VAMs} 2.0 framework is subjected to the firefly optimization process. In contrast, the method based on ABC (Artificial Bee Colony) optimizes over the ANN meta-model of PLL. ANNs have been found to produce more accurate outcomes with less optimization time than polynomial meta-models.
The following steps are taken into account:
The Intelligent Meta-Model Integrated Verilog-AMS (i_{VAM}) concept.
OP_AMP schematic design
Neural network-based intelligent meta-model generation.
The i_{VAM}-based Firefly algorithm
$Verilog_{AMS}$ neural network construction
ANN-based met-modeling and the ABC algorithm for quick and precise nano-CMOS mixed-signal design exploration.
An analog/mixed-signal circuit design optimization flow based on a non-polynomial meta-model is introduced.
Non-polynomial ANN and PD of 180nm CMOS PLL are used practically.
The PLL physical design is optimized using the ABC algorithm, which use the meta-model rather than the real circuit.
PLL can be demonstrated more quickly and accurately than the polynomial meta-model.
ANN and regression models for designing electronic circuits [2]: For improved precision, this specific method uses a circuit with four resistors whose values are continuously changed. The amplifier circuit determines the nominal values of the resistors. The resistor's values are switched from LOW to NOMINAL and back to HIGH. Following R1, R2, R3, and R4 variations, Gain $\Delta(V) and$ $\left(\frac{I_C}{I_B}\right)$ are calculated. The dataset is collected form the output and split into training and test set and the graph is Estimated ANN response surface for $\left(\frac{I_C}{I_B}\right)$
For these two outcomes, use the regression polynomial. Interaction effect plots are used to construct various datasets and graphs that display Gain $\Delta(V) and.$ $\left(\frac{I_C}{I_B}\right)$ acquired using the ANN. The ANN outperformed the traditional regression technique in terms of accuracy.

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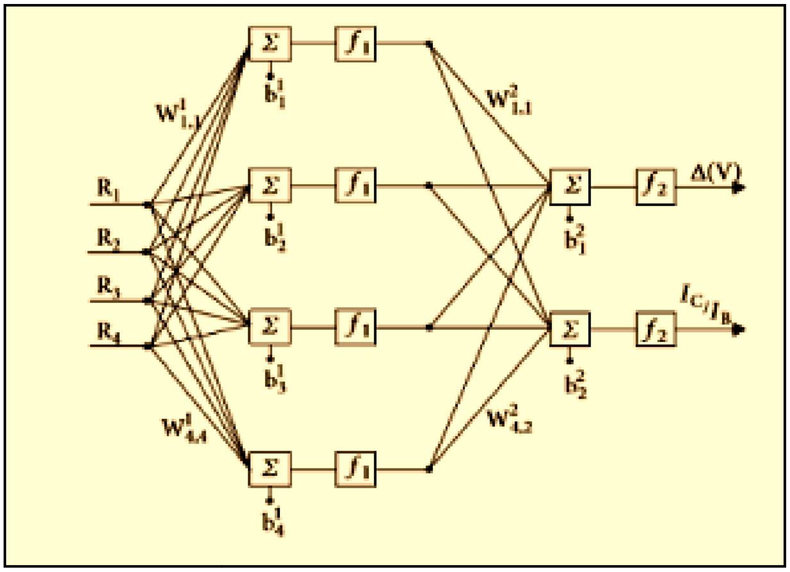

Fig. 3: ANN structure

MOM-SVM [3]: Support Vector Machine-based multi-output modeling. In essence, a VCO (Voltage Controlled Oscillator) is designed as a test circuit in Cadence Virtuoso, obtained using the SPICE simulator, and then tuned using the k-cross validation method. Additionally, MATLAB is utilized due to the utilization of LSSVM for modeling.

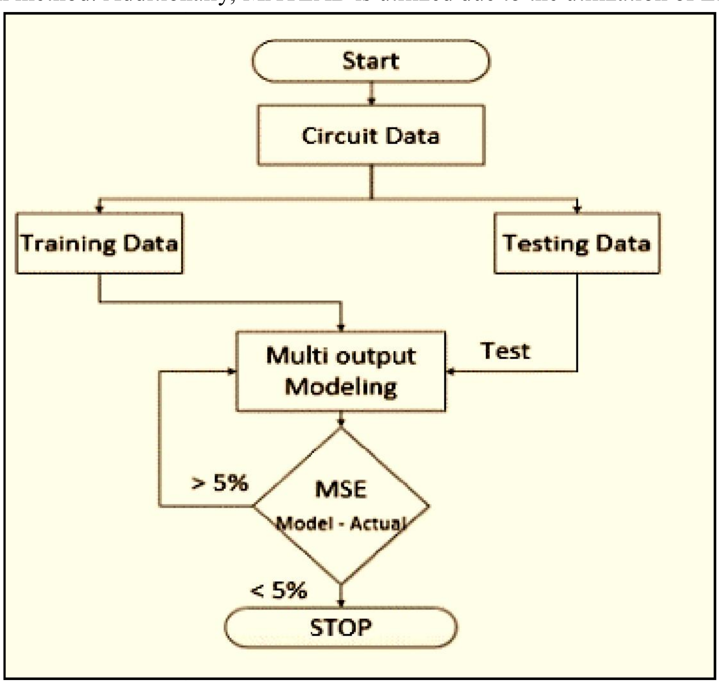

Fig.1: Flowchart for the MOM_SVM analog circuit [3]

Analog Circuit Design Regression Methodologies [5]: Saving simulation time with the least degree of accuracy loss is the primary goal here. Training error, build time, testing error, testing time, variable space, and training data set are the fundamental components of the regression approach; of these, build time, testing error, and testing time are the most crucial metrics. Due to their ease of use and training, Gaussian Processes are employed as regression techniques. The procedure consists of

GP Scikit: while using a noisy training dataset, it will smooth the prediction. Python is used to implement it.
GP Rasmussen: MATLAB is used to implement it.
GPLP Park: MATLAB is used to implement it.
SPGP: It will assist in selecting training datasets for pseudo-inputs. Python is used to implement it.
KRG: Scikit-learn uses Python to implement it.
KRC: During training, input space is divided using this method. Python is used to implement it.
Py XGPR: Python is used to implement it.
FFX: This Python implementation is used to forecast data.
RIWD: It improves prediction error and works with big datasets. Python is used to implement it.
Optimizing Analog Circuits using Error Margining and Sparse Regression [4]: For sample points, run Cadence Virtuoso. which first uses Sparse regression to construct linear models. Additionally, use the following to obtain the worst-case model equation:

$$g_{WC}^{l,u} = \sum_{i=1}^{n} \delta_i x_i \pm c - 3 * \sigma \geq G^{l,u}$$

Determine the parameters such as power consumption, gain frequency, gain, phase margin, slew rate, input offset, and output swing after drawing the circuit design (OP_AMP).
Determine the characteristics such as the noise figure, forward reflection, forward transmission, and reverse reflection after drawing the design of a separate circuit (a low noise amplifier).

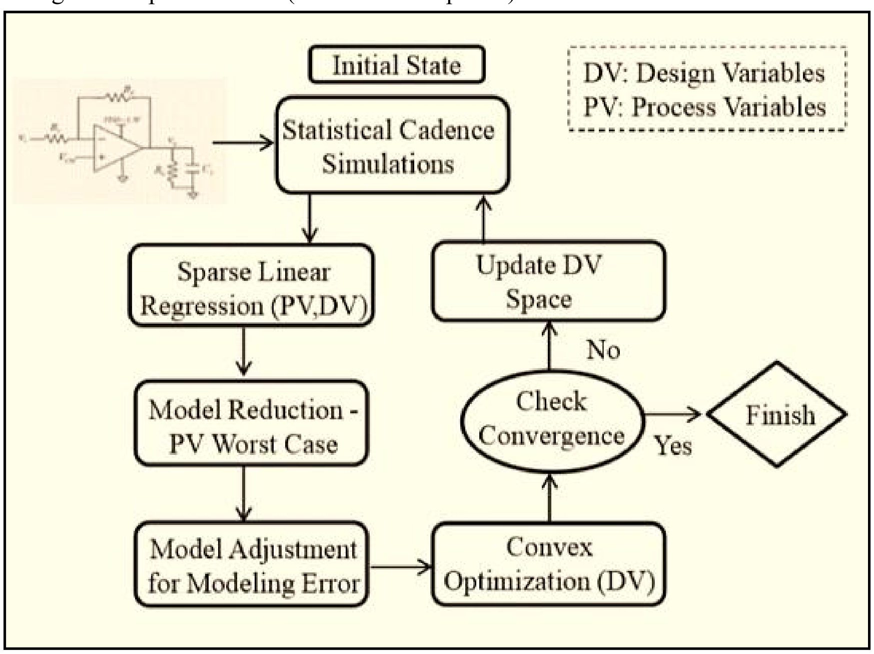

Fig.2: Flowchart for the method of analog circuit using Sparse Regression [4]

V. CONCLUSION

Because analogue means having multiple parameters and data, it is impossible to manually obtain the correct output if there are changes in the data (for example, a slight change in temperature). When there is a significant change in the data, such as when the input voltage fluctuates between 0.8 and 1.2 volts, the data will automatically adjust the output, making it impossible to manually update and modify the output each time. Therefore, machine learning is applied here. In machine learning (ML), we essentially train the machine to learn something using various languages, such as R or Python. Here, we have a dataset from the output that may be subjected to various machine learning topologies. For example, in regression, we have polynomials, decision trees, multiple regression, basic linear regression, and many more. We now have a number of parameters to examine, such as power consumption, delay, and accuracy, which is a crucial parameter when considering machine learning. For example, there are different sub-models within regression models, and in addition to that, there are various ANN and CNN models that are selected based on output accuracy. Therefore, as close loop as possible, we may reduce simulation time, improve accuracy, and implement a multi-output system.

REFERENCES

[1]. Saraju P. Mohanty Elias Kougianos. (2019). "Machine-Learning-Metamodel-Integrated Intelligent Verilog-AMS for Fast and Accurate Mixed-Signal Design Optimization", Xiv:1907.01526v1.

[2]. M. I. Dieste-Velasco, M. Diez-Mediavilla and C. Alonso-Tristán. (2018) "Regression and ANN Models for Electronic Circuit Design", *Hindawi Complexity Volume 2018, Article ID* 7379512, doi.org/10.1155/2018/7379512.

[3]. B.Shivalal Patro & Sushanta K. Mandal. (2017). "A Multi Output Formulation for Analog Circuits Using MOM-SVM", *Indonesian Journal of Electrical Engineering and Computer Science Vol*. 7, No. 1, July 2017.

[4]. Mohamed Baker Alawieh, Fa Wang, Rouwaida Kanj, Xin Li and Rajiv Joshi. (2016). "Efficient Analog Circuit Optimization Using Sparse Regression and Error Margining", *17th Int'l Symposium on Quality Electronic Design, 2016 IEEE*.

[5]. Ivick Guerra-G´omez, Trent McConaghy and E. Tlelo-Cuautle. (2015). "Study of Regression Methodologies on Analog Circuit Design", *Esteban Tlelo-Cuautle*, DOI: 10.1109/LATW.2015.7102504, 2015.

[6]. Anirban Sengupta & Saraju Mohanty. (2019). "VLSI Circuits and Systems Letter", *IEEE, Volume 5, Issue* 1, 2019.

[7]. Ramin M. Hasani, Dieter Haerle, Christian F. Baumgartner, Alessio R. Lomuscio & Radu Grosu. (2017). "Compositional Neural-Network Modeling of Complex Analog Circuits", *Internatinal joint conference on Neural Networks*, 2017.

[8]. Hao Cai, Jean-François Naviner, Hervé Petit. (2017). "Statistical Methods Applied to CMOS Reliability Analysis -A Survey", *HAL Id: hal*- 01570282, 2017.

[9]. Mriganka Chakraborty. (2012). "Artificial Neural Network for Performance Modeling and Optimization of CMOS Analog Circuits", *International Journal of Computer Applications* (0975 – 8887) Volume 58– No.18.

[10]. Li Yu. (2009). "Efficient IC Statistical Modeling and Extraction Using a Bayesian Inference Framework", *Massachusetts Institute of Technology*, 2009.

[11]. João Pedro da Silva Rosa. (2018). "Using Artificial Neural Networks to Size Analog Integrated Circuits", *Electrical and Computer Engineering*, 2018.