ML based PPA Push using XAI

Kyoungsun Cho, Mintae Lee, Jungho Kim, Sungyoul Seo,
Kibum Nam, Bonghyun Lee, Ki-ok Kim
Foundry Business, Samsung Electronics Co., Ltd.

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Motivation

- Design Space Exploration and Explanation

As the technology node scales down continuously, the complexity of the chip design has increased. The electronic design automation (EDA) tools also need to be flexible to handle the design complexity.

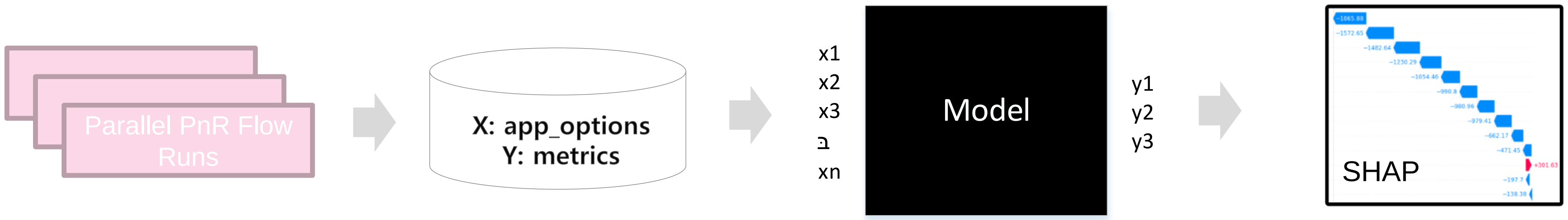
- Advanced EDA tools offer numerous tunable parameters that can greatly affect physical design quality.
- As the demand to achieve improved results (time to market) faster is growing, physical engineer faces challenges that are impossible to keep pace with conventional approaches taking months to manually tune parameters with hundreds of trials.
- Moreover, even if engineers manage to find the best recipe through vast design space exploration for a given design, it is likely to be a one-time solution that is difficult to apply to another design unless the influence of various parameters cannot be understood sufficiently.

Proposed Flow

- Prediction Model and Analysis Flow using XAI

Therefore, we propose an ML based PPA push work flow using XAI which not only we can obtain the golden recipe for a given design, but also help to understand the influence of the parameters used.

- Generate DOE automatically using Machine Learning-based EDA tools
- Build a Machine Learning-based prediction model using the results from multiple PnR runs
- Adopt SHAP, which is one of eXplainable AI(XAI) techniques, to allow engineer to select parameters in an optimal way and to provide an understanding the influence between parameters.



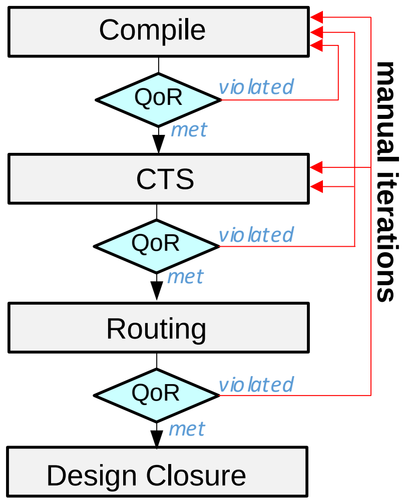
Overall Design Flow

Conventional Flow

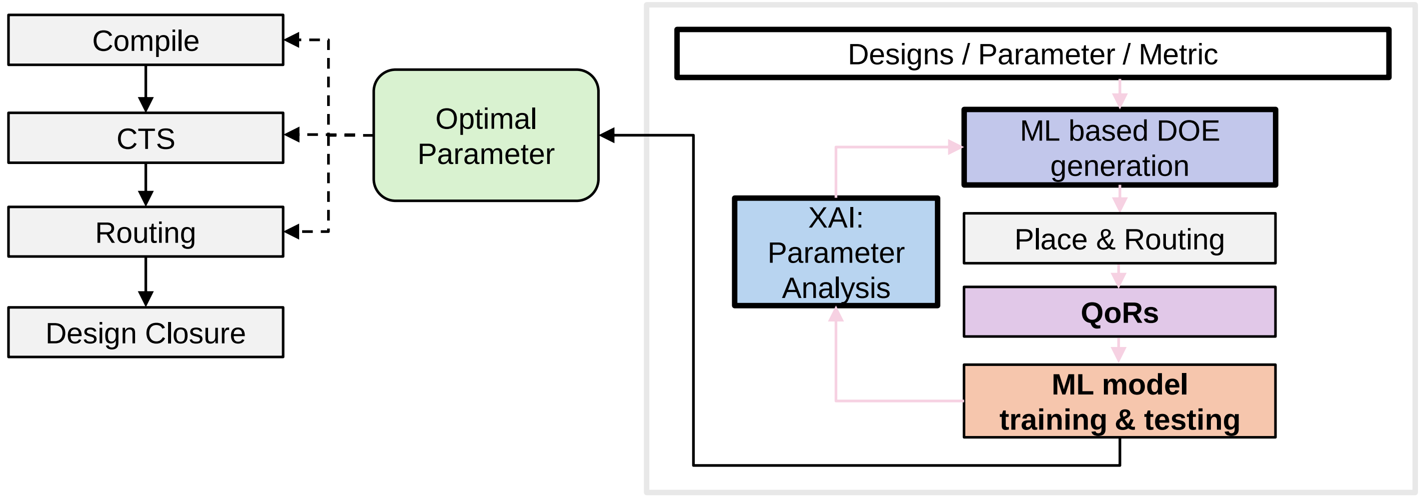
- Engineers need to perform the entire or part of flows iteratively by tuning various parameters
- Since EDA tools may have 100s, or even 1000s of parameters, selecting parameters' settings can be extremely complex and time-consuming task

Proposed Flow

- Train a ML model using the QoR dataset obtained from the parallel runs generated by ML based EDA tools.
- Select the important parameters affecting the QoR metrics which want to focus on through ML model and SHAP.
- Apply the fine-tuned parameter set to the target design.



< Conventional Flow>



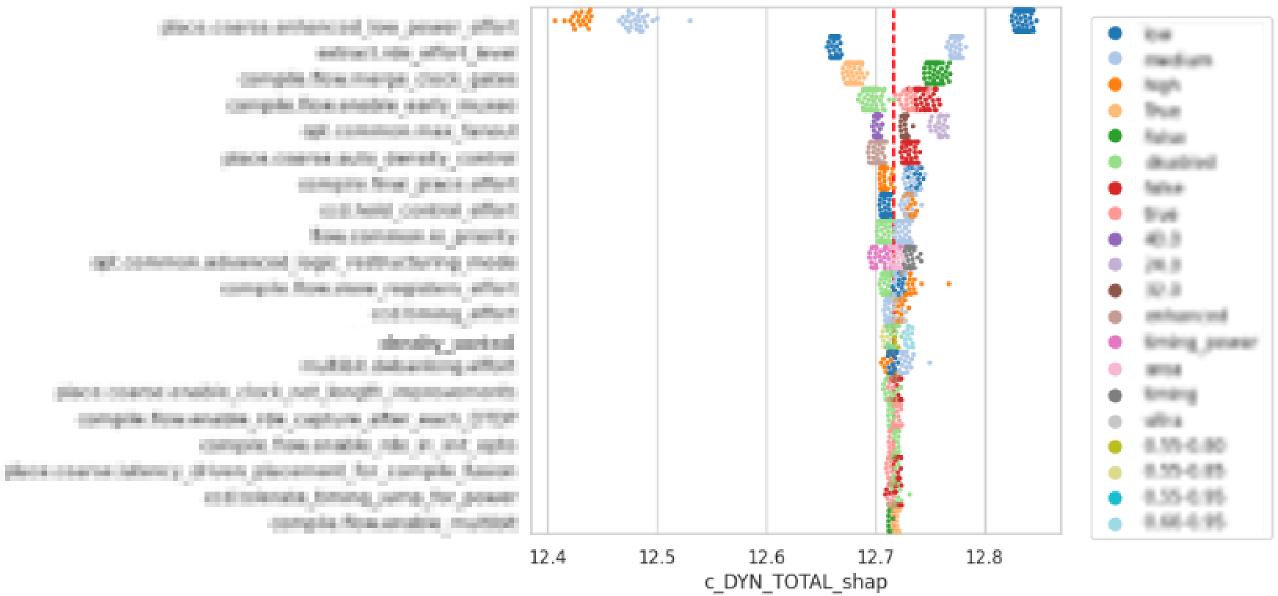
< Proposed Flow>

Prediction model

A parameter optimization flow that involves a prediction model and an XAI analyzer

- Using ML based EDA tool, create multiple scenarios automatically with design information, design target (e.g. power, frequency, area etc) and tool parameters
- Building a regression model using multiple run's QoR metrics as an output (Y) and tool parameter as an input (X).
- Since most tool parameters have the options of categorical values, CATBoost regressor is used as a model
- Parameter selection through Feature importance analysis using SHAP.
- SHAP swarmplot is summary to show how the prediction value of a QoR metic changes as the value of a single parameter changes. This can help to understand how the model is using each feature to make predictions.

Model explanation



<SHAP Swarmplot to identify Feature Importance>

X axis : SHAP value * baseline QoR value

Y axis : app_options (sorted by Feature Importance)

- The plot shows which features have the biggest impact on the model's prediction and it help to identify any feature are redundant or less necessary.
- Each dot corresponds to an individual configuration used in the experiment.
- The x-axis represent how did this input feature impact the final prediction on the objective (in this case, SHAP value of Dynamic Total power).
- The input features are listed on the y-axis and sorted by their importance. The higher it is, the more influential the parameter has.
- For each input features, it needs to pick the parameters that are split left and right clearly to be able to identify a negative impact(left) or a positive impact(right) on the objective.

[beeswarm plot — SHAP latest documentation]

[Your intuitive guide to interpret SHAP's beeswarm plot]

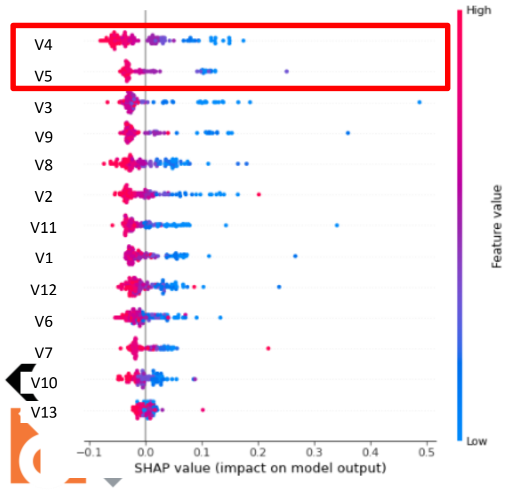
Experiment Results (1)

- Case1: More delicate parameter tuning

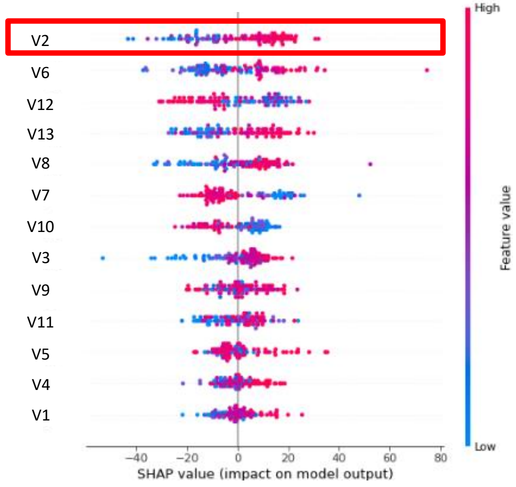
Able to achieve power gain of 1.8% with 2nm industrial block

- Engineers already knew that increasing via parameter would reduce the wire length and thus the switching power. However, since if the parameter value increased beyond a certain level, the DRC violations also increased, it was necessary to adjust the parameter value per individual via.
- Generated 120 runs in total and built the regression model with dynamic power, wire length and # of DRV as outputs and via parameter as input features. And then analyzed the feature importance using SHAP.
- Consequently, higher V4/V5 and lower V2 via parameter, we could get less total power by switching power reduction. Especially, V2 trend were newly caught by the proposed work flow.

Dynamic Power



DRC



	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13
Expert Engineer's parameter	3.5	3	3.5	3.5	3.5	2.5	2.5	2.5	2.5	2.5	2.5	3.5	2.5
ML model picked parameter	4	2.5	3.5	5	4.5	3.5	4	4.5	4.5	4.5	5	4.5	2

Status	FREQ	INTERNAL	SWITCHING	LEAKAGE	TOTAL POWER	# DRV	WIRELENGTH
Baseline*	100	100	100	100	100	100	100
ML model picked parameter*	101.0	99.5	97.8	98.6	98.2	58.8	98.8
Improvement	1%	0.5%	2.3%	1.6%	1.8%	41.2%	1.2%

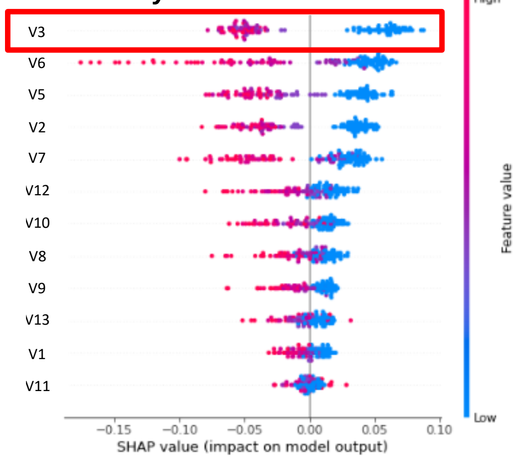
*Normalized value

Experiment Results (2)

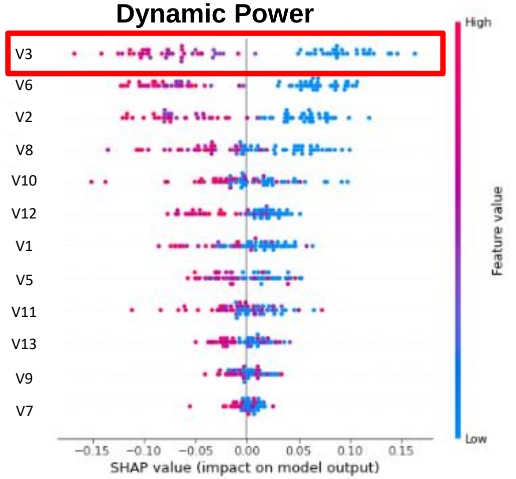
- Case2: Common influential feature identification

Able to identify the most influenced feature that can be commonly used.

- The proposed analysis flow was applied to 3 different designs using the same process.
- Generated 120 runs per design and built the model respectively which used dynamic power as outputs and via parameter as input features. And then analyzed the feature importance through SHAP.
- The result shows that the power improves (1.76%~5.45%) in all three blocks when the parameter values are chosen in a direction that hinders elevation to upper metal layers using higher parameter values for V3~V6.



< Design A>



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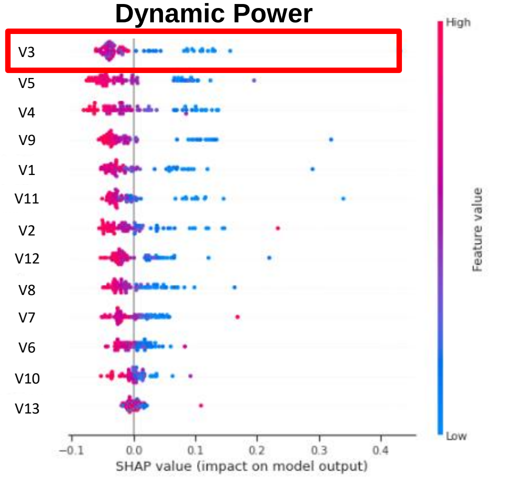

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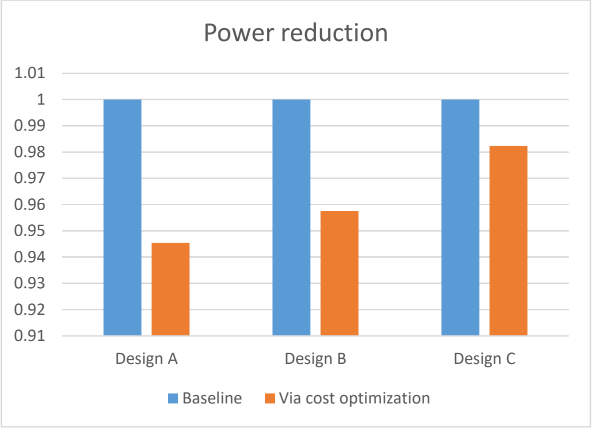
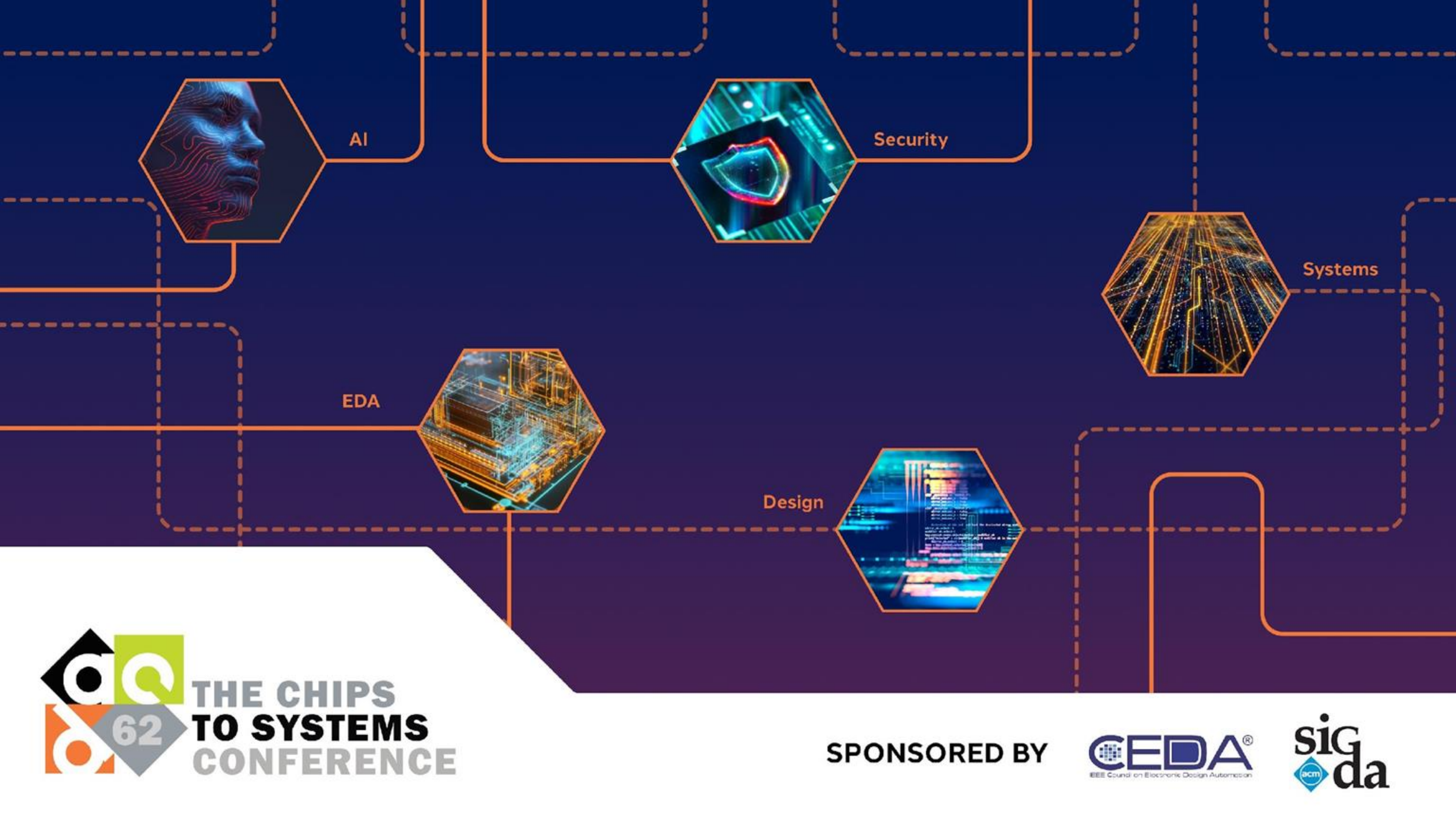


< Power gain per design >

*Normalized value

Summary

- Proposed ML Based PPA push work flow using XAI can reduce manual search, comparing and learning in multiple experiments. This workflow gives us the best way to tune multiple parameters in an efficient way to achieve best Power, Performance, Area and Cost.
- This approach provides an explanation to the use that justifies its recommendations, decision. The user can understand and decide based on the explanation
- In this work, we demonstrate that P&R with the proposed work flow can achieve 1.8% power gain and reduce # of DRV by 41.2%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