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Meta-Modeling Using Prediction Correlation for Solar Powered Battery Charge- Discharge System for a Wireless Sensor Node

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Abstract: Wireless sensor nodes to be powered continuously for long life, good performance and high accuracy in the unattended location of the world. Battery powered sensor nodes are not able to provide continuous power. solar power is the scavenge source, but due to the sun cycle variation, it is important to predict the solar current energy produced according to time.In this paper we use automatic battery charger -discharge system that uses the meta-modelling correlation for prediction of solar energy and processor is designed for powering wireless sensor node. The new method uses simple kriging model and swarms optimization that improves precharge time by 61.54% while speeding up the process by390*. The simulation results are shown by MATLAB, LabVIEW and design of the processor with EDA tools.

Keywords: Wireless Sensor, MATLAB, LABVIEW.

1. INTRODUCTION

Battery capacity is limited by time. Energy management has always been an important issue. Wireless sensor nodes powers by solar energy are the fastest way to use the scanevage source. But predicting the solar energy by varying sun cycle always been in the experimental part. The current produced by the solar plate should be normalized by the processor before entering the node. By continues powering the sensor node brings excellent computing power to the network system. Sun cycle changes with time so we can't predict the energy. This paper introduces the Meta-modelling using prediction correlation for designing the processor and battery charger and discharging system for battery management. The main purpose is to achieve energy management. For creating meta-models Kriging methods are used. The local departure function is a correlation function that accurately models the nano scale effects, making Kriging metamodels process aware and robust for high-dimensional designs. Meta modeling based optimization design using Kriging prediction techniques has been used in VLSI[4]. It is a method that combines meta models and optimization algorithms for fast design optimization of analog/mixed-signal circuits. The speedup comes from the use of metamodels, automatic optimization algorithms, and elimination of multiple manual layout steps[2]. The meta-models are then optimized using a simulated annealing-based algorithm.

2. FUNDAMENTALS OF KRIGING

It was originally used in geo statistics fields for mining purposes. Each point is predicted based on a set of unique weights (λj).
Two methods are considered

1. Ordinary Kriging
2. Simple Kriging

The main idea behind Kriging is that the predicted outputs are weighted averages of sampled data. The weights are unique to each predicted point and are a function of the distance between the point to be predicted and observed points.The general expression of a Kriging model is as follows[3]:

$$y(\mathbf{x}_0) = \sum_{j=1}^{M} \lambda_j B_j(\mathbf{x}) + z(\mathbf{x})$$

Where y(**x0**) is the predicted response at design point **x0**,{Bj (**x**), j = 1, . . . ,M} is a specific set of basic functions over the M-dimensional design domain DM, λj are fitting coefficients (or Weights) to be determined, and z(**x**) is the random process error. In simple Kriging, a constant and known mean over the global domain is assumed to the predicted point. It is assumed that the process has a mean μ, variance σ2, and correlation function called the variogram in geo statistics, r (**s**, **t**) between point's **s** and **t** was given by

$$r(\mathbf{s}, \mathbf{t}) = \mathrm{Corr}(z(\mathbf{s}), z(\mathbf{t})).$$

The variogram is used to derive the Kriging weights λj. The autocorrelation of the design points is characterized by the covariance function. The weights are chosen so that the Kriging variance is minimized. One advantage of Kriging is that the estimated response at sample points is exactly the same as the observed.

Estimation of the correlation between sampled points and a predicted point is done with the semivariogram model. Based on the nature of the observed data points, the empirical model could be fitted to spherical, linear, Gaussian, or exponential theoretical models.

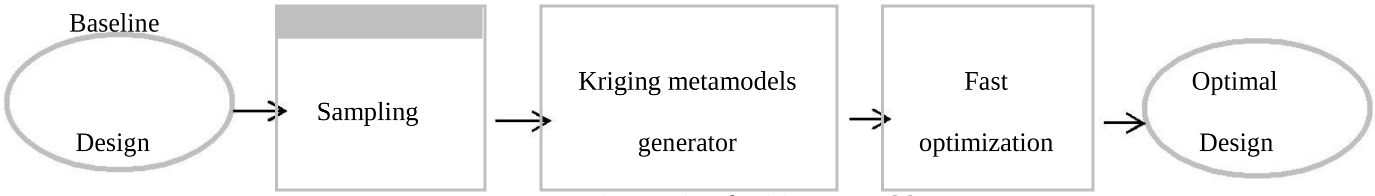

Fig2.1 Design of Kriging Met model

2.1 KRIGING-BASED FAST METHODOLOGY

Meta-models are used to increase the efficiency of the design optimization while maintaining sufficient accuracy. Kriging methods, which take into account the correlations among design parameters, are excellent prediction models for complex designs with high dimensionality.

2.2.1 Parasitic-Aware Netlist Generation and Parameterization

The starting point of the flow is a parasitic-aware Netlist extracted from the physical layout design and used in order to achieve silicon-level accuracy. Design (length L and width W) and process (threshold voltage Vth and oxide thickness (Tox)) parameters are identified in the parasitic-aware Netlist, which is then parameterized with respect to these variables for an automatic sample-point generation. The parameterization ensures that the layout design does not have to be physically redrawn during each iteration. The main assumption is that the resizing of the devices does not perturb the interconnect significantly. We call this on-the-fly automatic layout-accurate Netlist resizing as "virtual resizing."

2.2.2 Accurate and Fast Design Space Sampling

Uniform Sampling

Latin Hypercube Sampling (LHS) and Middle Latin Hypercube Sampling (MLHS) techniques are common uniform sampling techniques. There are also many variations which are derived from these two, such as orthogonal array-based LHS, symmetric LHS, orthogonal column LHS, and optimal LHS. [5]

Uniform sampling results in more even distribution which usually has a large effect if the number of samples is small. Given that the points are more evenly spaced in the domain T this dispersal of points produces more efficient coverage than random sampling. Uniform sampling techniques can deal with a large number of runs and design parameters. They also are computationally cheap to generate. Both LHS and MLHS sampling approaches divide the domain T into n amount of Latin squares, and a data point is then sampled from each square. The drawback for both designs is that the smallest possible variance for the sample mean can never be reached.

Latin Hypercube Sampling

Latin Hypercube Design produces a random point within the generated amount of Latin squares on the domain T. This technique provides more evenly distributed sampling points than random sampling techniques, but the samples can still be clustered together as the samples are taken randomly from each Latin square and they can be adjacent to each other.

Middle Latin Hypercube Sampling

The Middle Latin Hypercube Sampling (MLHS) technique is very similar to regular LHS. It divides the domain T into n amount of Latin squares, but instead of randomly sampling from each of those squares; it picks the middle value from each one. This technique is more uniform than the LHS. The main drawback is that it is not able to sample the regions close to the edge of the design space results for LHS

Design of Experiments Sampling

The design of Experiments (DOE) is a technique that is used with a large number of variables to profile and generate a predictive function of the model. Latin hypercube sampling (LHS) is used for generating sample design points. LHS covers all input dimensions simultaneously, thus improving the variance compared to random Monte Carlo distributions. The variance of the mean y LHS of a function f(x) over nLHS sample points is given by *v*

$$\mathrm{Var}(\overline{y}_{\mathrm{LHS}}) = \frac{1}{n}\mathrm{Var}(f(\mathbf{x})) - \frac{k}{n} + o\left(\frac{1}{n}\right)$$

Where *k* is a positive constant, shown to be smaller than the variance of random samples. A comparison of sampling techniques and sample sizes was performed, and LHS was preferred. The LHS sample point responses are generated using analog simulations and are fed into the Kriging Meta model generator. *L* and *W* are used as design parameters, while the process parameters are varied to model the effects of process variation.

3 Simple Kriging Metamodel Generation

The generated metamodel is a function of the design parameters L and W and the process parameters. In this paper, meta-models are generated using Wn and Wp. Precharge time TPC, sense delay. TSD, average power PSA, and sense margin VSM. Each FoM can be expressed in terms of the general form of the Kriging function. For example, the predicted precharge time Ypr at an unknown design point W∗n is expressed as follows:

$$\widehat{Y}_{pr}\left(W_n^*\right) = \sum_{i=1}^{N} \lambda\left(W_n^*\right)_i Y_{pr}\left(W_{n_i}\right)$$

3.1 Kriging Algorithm

Simple Kriging-Based Metamodel Generation for Various FoMs of the Clamped Bitline Sense Amplifier

1. Obtain the target specifications of the CBLSA design and select the performance objectives or FoMs.
2. Create the parameterized parasitic-aware netlist of the CBLSA circuit after performing the baseline physical design, DRC and LVS verification, and RCLK extraction.
3. Initialize the number of sample set points (*n*).
4. Generate *n* sample set points using LHS.
5. Obtain *n* sample points *D* = [*D*1, *Dn*] for *M* design variables using LHS.
6. Derive variogram model for each FOM based on the observed sample points.
7. For Each design, point to be predicted. do
8. Generate the variogram for simple Kriging.
9. Generate prediction weights for simple Kriging.
10. Generate simple Kriging models for design points.
11. end for
12. Perform accuracy analysis of the simple Kriging meta models using the root mean square error (RMSE) and the correlation coefficient R2.

3.2 Simulated Annealing Algorithm

1. Initialize iteration counter: counter ← 0, Temperature: _ and Cooling Rate, and start from a solution_CBLSA*i*.
2. Calculate FoMs for_ CBLSA*i* from Kriging metamodels.
3. Consider the objective *T*PCi. result in ← _*T*PC ← *T*PCi .
4. While (_*T*PC! = 0) do
5. Counter ←max_Iteration.
6. While (counter >0) do
7. Make a random walk from _ CBLSA*i* to _ CBLSA*j*.
8. Calculate FoMs for_ CBLSA*j* using the metamodels.
9. if (*T*PC *j* <result) then
10. result ← *T*PC *j* . _ CBLSA*i* ← _ CBLSA*j* .
11. else
12. _*T*PC←*T*PCi− *T*PC*j* .
13. if *(* _*T*PC <0, random*(*0, 1*)* < *e* _*T*PC *T)* then
14. *T*PC*i*← *T*PC *j*. _ CBLSA*i*←_ CBLSA*j*.
15. End if
16. End if
17. Counter ←counter − 1.
18. End while
19. _← _ × Cooling Rate.
20. End while
21. return result and _ CBLSA*i*

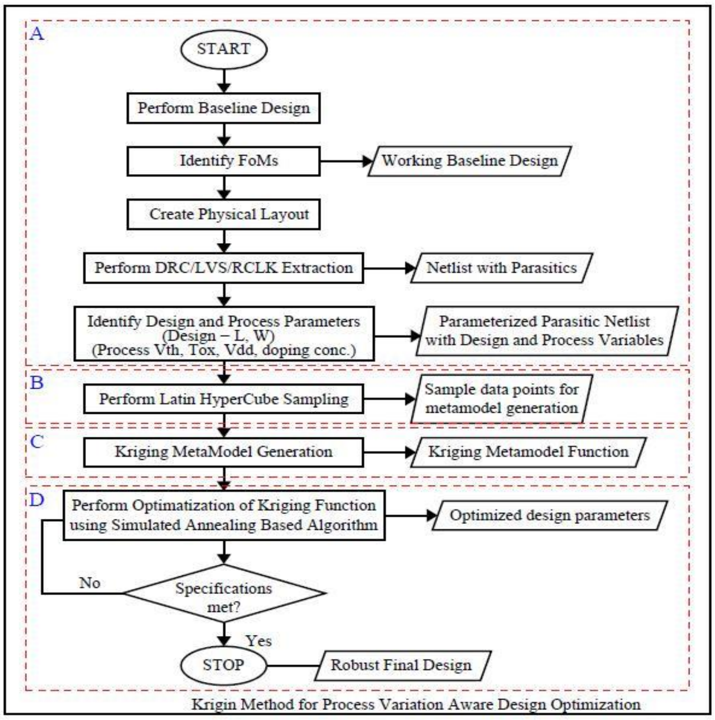

Fig 3.2: Kriging method for Design optimization

3.3 Algorithm for Optimization over Kriging Meta-models

A simulated annealing-based algorithm is proposed to optimize the simple Kriging metamodels of the CBLSA. [1]
The meta-models can be optimized for each of the identified FoMs. In this paper, the precharge time (*T*PC) is used as the objective, while the average power consumption (*P*SA) is used as a design constraint. The optimization steps are presented in Algorithm 2. The algorithm used to generate the Kriging metamodels was written using MATLAB with the help of the toolboxes mGstat [6] and SUMO [7].

3.4 Generation of Simple Kriging metamodels for the FoMs

Each Kriging predicted point is calculated with a different weight. A parametric analysis using *Wn* and *Wp* as variables shows that the circuit characteristics are dominated by *Wn*. [8]

The topology of the HCSA circuit supports this trend, as there are 10 nMOS transistors compared to 2 pMOS transistors. The operation of the circuit thus is more dependent on the variation of the nMOS transistor widths.

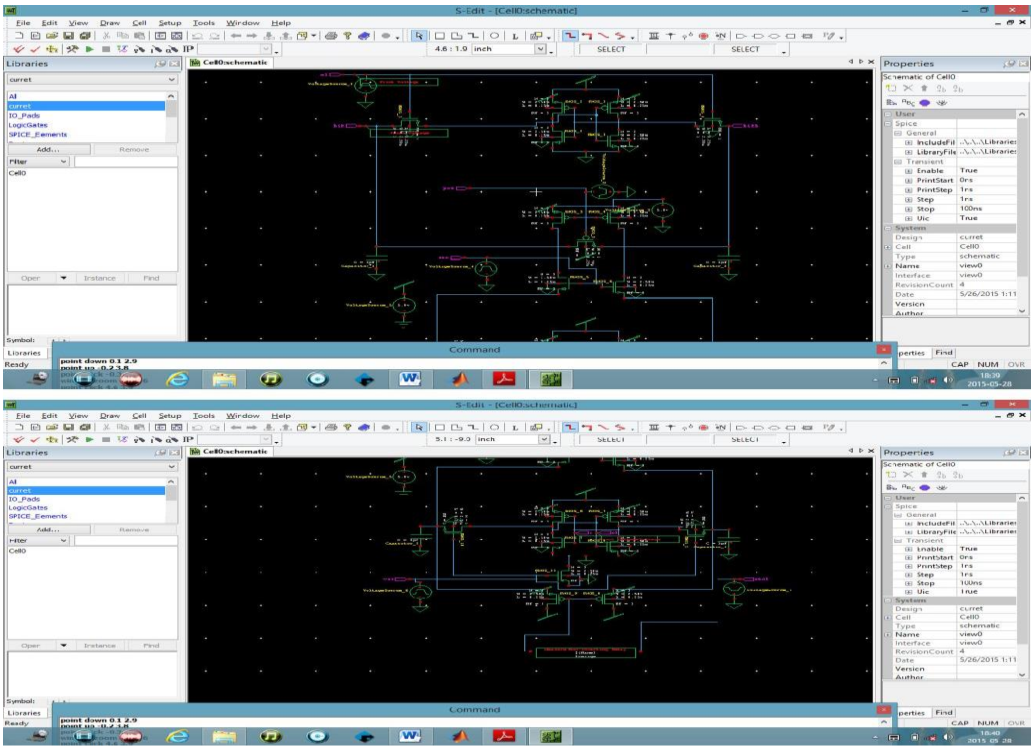

Fig 3.2: Schematic of HSCA

3.5. Accuracy Analysis of Simple Kriging Meta-models

An exhaustive simulation was performed to compare the accuracy of the Kriging metamodels. A total of 1000 design points were simulated to densely capture a golden surface in the design space. A statistical analysis for the meta models shows that the accuracy is very high. A summary of the statistical analysis of the meta-models for two-variable Kriging metamodels generated with 100 sample points. The metrics used for analysis are the RMSE and the correlation coefficient R2.The correlation coefficient R2 (also known as the cross-correlation coefficient) gives the quality of the least squares fitting compared to the original data. It essentially gives an estimate of the confidence level or how well the predicted metamodel will perform. A complete correlation gives R2 of 1, so the closer R2 is to 1, the more accurate will be the metamodel. From an analysis of the results, it is seen that the predicted points have an average R2 of 0.97. The simulation time for the generation of the simple Kriging metamodels was approximately 10.5 min for the two-variable meta model compared to 72 h for an exhaustive simulation.

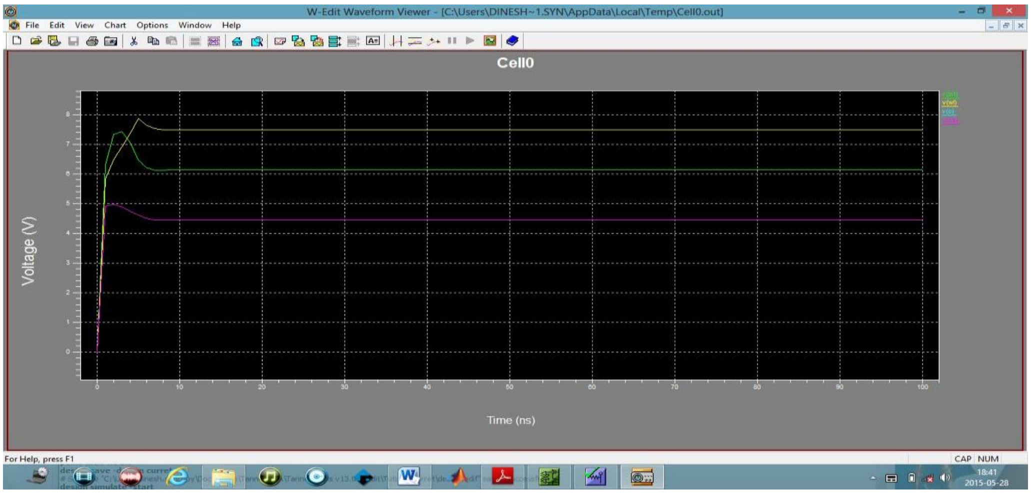

FIG 3.3: Waveform output of HSCA

A continuous signal is first sampled into a discrete signal. The discrete signal is again sampled at small intervals for evaluating the original amplitude of the signal. Particles are moved around in the search space. It searches all the path and estimates the path which provides the minimum critical path delay. Each time the wire size should be updated.

3.1.3 HCSA Optimization Results

Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here particles and moving these particles around in the search space according to simple mathematical formulae over the particles position and velocity.

Each particle's movement is influenced by it local best-known position but is also guided towards the best-known positions in the search space, which are updated as better positions are found by other particles. This expected to move the swarm toward the best solutions.
A basic variant of the PSO algorithm works by having the population (called a swarm) of candidate solutions. These particles are moved around in the search space according to few simple formulae. The movements of the particles are guided by their own best-known position in the search space as well as the entire swarm's best-known position. When improved positions are being discovered the will then come to guide the movement of the swarm. The process is repeated and by doing so it is hoped that a satisfactory solution will eventually be discovered. Let f. be the cost function which must be minimized. the function takes a candidate solution as an argument in the form of a vector of real numbers and produces a real number as output which indicates the objective function value of the given candidate solution. Let S be the number of particles in the swarm, each having a position xi ∑ n in the search space.

4. Automatic Battery Switching System (ABSS)

Power optimized fully controlled, and solar powered charging and discharging system with the pack of two rechargeable batteries. It involves the switches S1, S2, S3, S4 and S5 to control the Automatic Battery Switching System (ABSS). The switch status for charging and discharging the battery 1 and battery 2 respectively is listed in Table 1The design proposed in this research involves two separate rechargeable battery units working alternately. Thus, when the first battery gets the power from the solar system, the second battery delivers sensor node by all the power required by it. But, in a general conventional wireless sensor network, the power source is used to recharge only a single battery.

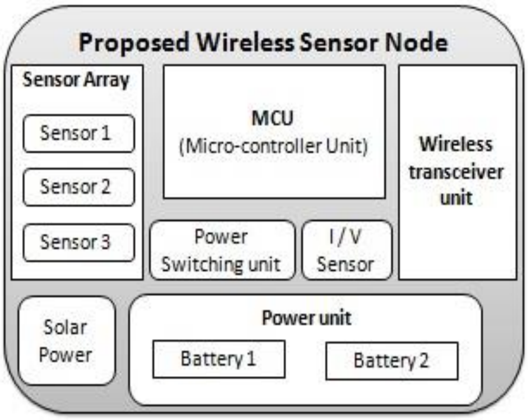

Fig 4.1: Wireless sensor node with solar power and meta-modeling processor

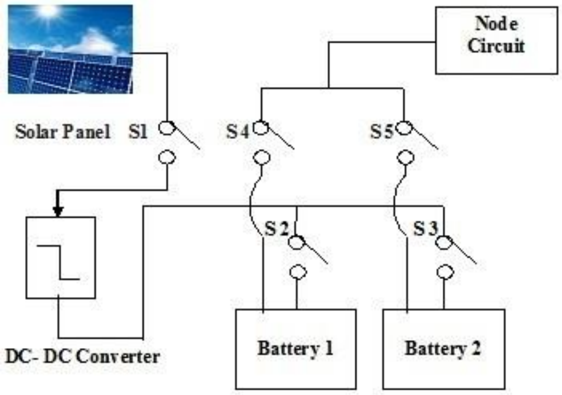

Fig 4.2: Battery Charging and Discharging System

The BCDS (Battery Charging and Discharging System) is a key element which connects the charging and discharging paths between the batteries and the wireless sensor node. This BCDS system is given two power sensors for the batteries to check the availability of the power in them. According to the power status data sets the BCDS will take care of two major works. In its first work it will route the power from the solar system to the battery which is being to be charged and in its second work, it routes the battery which has to take care of powering the system to the sensor node. In order to do this works efficiently the BCDS unit follows the set of conditions which are used to control the paths for the charging and discharging process as it in Table1. In the first condition, BCDS is charging battery 1 and discharging battery 2. In the second condition, BCDS is charging battery 2 and discharging battery 1. BCDS is set to supply the sensor node directly from the solar power if both the batteries are fully discharged. This system consists of a DC–DC synchronous rectified converter and the charger unit controlled by a PWM signal which is applied to one of its terminals and supplies each battery according to a programmed algorithm in the microcontroller. Between the solar panel and the Battery charger system, there are a voltage conditioning capacitor and I/V sensor from Autopilot with 0–3.3 V output6. The capacitor prevents the voltage at the charger input pin from falling below the charge voltage of the battery cells when solar power is not capable of providing appropriate voltage level. The role of I/V sensor is detecting the current and voltage levels that solar panels provide to the charger device.

5. Metamodeling processor

Metamodeling

Conventional methods of battery life management, which deals with regulating the protection, charging and monitoring of the battery, are ineffective for two reasons. First, they do not predict the battery charge level and second, they require the battery to be off-line for the period of the measurements of the battery parameters. The proposed battery models advance by combining elements of adaptive and static battery management techniques. The use of **Metamodeling processor** empirically derived constants for battery management. **Metamodeling processor** gets power availability in the two batteries and it takes the decision that on which battery the wireless sensor node will get the power.

Power Results:

VVoltageSource_5 from time 0 to 2e-006
Average power consumed -> 3.102333e-006 watts
Max power 3.619108e-005 at time 1.276e-006
Min power 0.000000e+000 at time 0
Measurement result summary
TRAN_Measure_Delay_1 = 0.1009n

Table 1: Battery Charging and Discharging

Charge/Discharge Condition		Switch Conditions				
Battery 1	**Battery 2**	**S1**	**S2**	**S3**	**S4**	**S5**
Charge	Discharge	ON	ON	OFF	OFF	ON
Discharge	Charge	ON	OFF	ON	ON	OFF

Table 2: Primary batteries verus solar cells

Energy Source	Power Density	Power supply size	
		Continuous Operation	**Periodical Operation**
Solar Outdoors	1.42 mW/cm^2	76 cm^2	0.078 cm^2
Solar Indoors	0.017 mW/cm^2	6480 cm^2	6.7 cm^2
Battery	0.018 mW/cm^3	5913 cm^3	6.1 cm^3

CONCLUSIONS

This proposed Research focused on introducing the 4th generation power supply management and controlled by advanced VLSI technology with the inbuilt energy harvesting system. , **Metamodeling processor** is in the best position to provide better efficiency.

Thus it provides a high-performance energy management system for wireless sensor node for while comparing with single battery energy harvesting system. The replacement time of the battery is increased and the effort need for battery monitoring is decreased. Compared with conventional battery management techniques, the proposed research effectively avoids the frequent replacement of batteries in the sensor node about 95%.

This method improves precharge time by 61.54% while speeding up the process by390*. The simulation results are shown by MATLAB, LabVIEW and design of the processor with EDA tools.

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