



In this paper, we propose CyberPhysical-system-on-chips (CP-SoC), a novel architecture and design paradigm that combines a sensor-actuator-rich self-aware computing-communication-control (C3) centric platform. CPSoC deploys an adaptive & reflective middleware (a flexible hardware-software stack and interface between the application and OS layer) to control the manifestations of computations (e.g., aging, overheating, parameter variability etc.) on the physical characteristics of the chip itself and the outside interacting environment. Inspired by the C3 paradigm of CPSs [4] and adaptive and learning abilities of autonomous computing [5], CPSoC provides a computing framework that addresses and assures the dependability of the cyber/information processing (i.e., the cyber aspects such as integrity, correctness, accuracy, timing, reliability and security) while simultaneously addressing the physical manifestations (in performance, power, thermal, aging, wear-out, material degradation, and reliability and dependability) of the information processing on the underlying computing platform. CPSoC aims to coalesce these two traditionally disjoint aspects/abstractions of cyber/information world and the underlying physical computing worlds into a unified abstraction of computing by using cross-layer virtual/physical sensing and actuation to enable a C3 centric self-aware computing platform.

## II. ARCHITECTURE OF CPSoC

The CPSoC architecture consists of a combination of sensor-actuator-rich computation platform supported by adaptive NoCs (cNoC, sNoC), Introspective Sentient Units (ISU), and an adaptive & reflective middleware to manage and control both the cyber/information and physical environment and characteristics of the chip. The CPSoC architecture is broadly divided into several layers of abstraction, for example, applications, operating system, network and bus communication, hardware, and the circuit / device layers. CPSoC inherits most features of MPSoC in addition to on-chip sensing and actuation to enable the ODA paradigm. Unlike traditional MPSoC, each layer of the CPSoC can be made self-aware and adaptive, by a combination of software and physical sensors and actuators as shown in Fig. 1a. These layer specific feedback loops are integrated into a flexible stack which can be implemented either as firmware or middleware as shown by the dotted line in Fig. 1a.

CPSoC distinctly differs from a traditional MPSoC in several ways. Traditional MPSoC paradigms lack the ability to sense the system states and behaviors across layers of system stack due to lack of architectural support; they are incapable of exploiting and exposing process and workload variations due to lack of suitable abstractions at multiple layers. Furthermore, they sacrifice usable performance and energy opportunities by adopting worst case design (guardbands), and lack support for multi-level actuation mechanisms and adaptations to aggressively meet competing and conflicting demands. Moreover, traditional MPSoCs lack self-learning mechanisms that can anticipate failures and predict vulnerabilities. CPSoC overcomes these limitations as detailed below.

## III. ATTRIBUTES AND FEATURES OF CPSoC

The CPSoC framework supports four key ideas: 1) physical and virtual sensing and actuation 2) self-awareness and adaptation 3) multi or cross-layer interactions and interventions 4) predictive modeling and learning. We briefly describe these below. (A detailed description is in our Technical Report[6].)

### A. Cross-Layer Virtual and Physical Sensing & Actuation

CPSoCs are sensor-actuator-rich MPSoCs that include several on-chip physical sensors (e.g., aging, oxide breakdown, leakage, reliability, temperature, performance counters, as well as voltage, current, and power sensors [6]) on the lower three layers as shown by the on-chip-sensing-and-actuation block (OCSN) in Fig. 1b and tabulated

in Table I. On the other hand, **virtual sensing** is a physical-sensor-less sensing of immeasurable parameters using indirect computation. It's a software sensor that provides indirect measurement of abstract conditions, contexts, inferences or estimates by processing (e.g., combining, aggregating, or predicting) sensed data from either a set of homogeneous or heterogeneous sensors. It's a computational technique that enhances and/or adds sensing capability, introduces sensing options, increases sensitivity, enables efficient sensor resource uses, and overcomes physical placement and cost restrictions. When combined with different kinds of sensors, virtual sensing enables consensus to resolve faults and errors while providing a test bed for on-chip sensor fusion. The need for such an over-provisioned sensing architecture for MPSoCs has also been identified by Intel [7].

Table I  
VIRTUAL/PHYSICAL SENSING AND ACTUATIONS ACROSS LAYERS

Layers	Virtual/Physical Sensors	Virtual/Physical Actuators
Application	Workload type, code features, func. complexity (cyclomatic), power, energy, Execution time,	Loop perforation, memoization Algorithmic Choice, Degree of Parallelism, code redundancy
Operating System	System Utilization, Epoch length, Context Switch Counter, Thread load, History	Task Allocation, Scheduling, Migration, Offloading, Duty Cycling, Mem. Page Allocation
Dynamic Compilation & Virtualization	Code profiling stats, Instruction Groups, program phases, access patterns, critical instructions,	Data and code transformation (equivalence, multiplicity, rel. position, stack & heap size)
Hardware Architecture	Cache misses, Miss rate; access rate; branch miss, TLB misses, IPC, ILP/MLP, Core asymmetry	Cache Sizing; Reconfiguration, Resource Provisioning, Static/Dynamic Redundancy
Network/Bus Communication	Bandwidth; Packet/Flit status; Channel Status, Congestion, Latency, bus / router power	Adaptive Routing, Dynamic Bandwidth Allocation Ch. no and direction
Circuit/Device	Ckt Delay, Aging, leakage, Power, Temperature, oxide breakdown, Reliability	DVFS, ABB, Reverse Biasing, Clock & power-gating, Multi-gate thresholding,

Similarly, we define **virtual actuations** [6](e.g., application duty cycling, algorithmic choice, checkpointing) that are software/hardware interventions that can predictively influence system design objectives such as performance, power, and reliability. Virtual actuations can be combined with physical actuation mechanisms commonly adopted in modern chips (e.g., DVFS and adaptive body biasing (ABB) to control the chip performance, power, and parametric variations); the notion of actuator fusion in CPSoC represents virtual and physical actuations that are combined across different layers of abstraction [6].

### B. Self-Awareness and Adaptation

Self-awareness is used to describe the ability of the CPSoC to observe its own internal behaviors as well as external systems it interacts with such that it is capable of making judicious decisions that optimize performance and other quality of service (QoS) metrics [5]. Self-aware systems will be capable of adapting their behavior and resources to automatically find the best way to accomplish a given goal despite changing environmental conditions and demands. A self-aware system must be able to monitor its behavior to update one or more of its components (hardware architecture, operating system and running applications), to achieve its goals. Similar efforts on self-awareness and adaptation are being pursued by other researchers including [8], [9], [10].

### C. Multi or Cross-Layer Interactions and Interventions

Two key attributes of the self-aware CPSoC are adaptation of each layer and multiple cooperative ODA loops. As an example, the unification of an adaptive computing platform (with combined DVFS, ABB, and other actuation means) along with a bandwidth adaptive NoC [6] offers a completely different approach (extra dimensions of control) and solutions in comparison to traditional MPSoC architecture. These cooperative and hierarchical control loops –e.g., the combination of traditional control loop (dotted lower box in Fig. 2) together with virtual sensing enabled optimized loop (upper

loop in Fig. 2) – effectively translate user goals or QoS into one or more multiple design objectives [6].

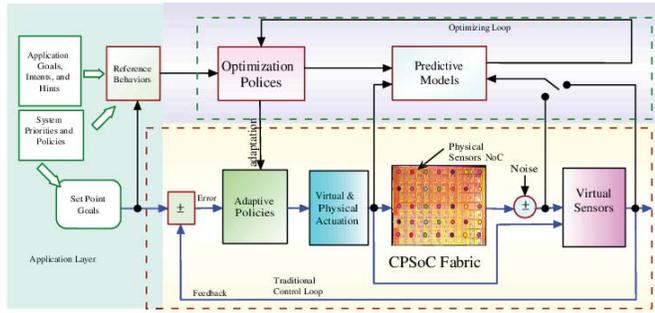


Figure 2. Adaptation using predictive control model and policies in CPSoC.

#### D. Predictive Modeling and Learning

Predictive modeling and learning abilities of the system behavior as well as internal and external (environmental) states provide self-modeling abilities in the CPSoC paradigm. The system behavior and states can be built using on-line or off-line linear or non-linear models in time or frequency domains [11]. We specifically use statistical and neural network approaches [12], [13] such that the model accuracy can be traded-off for model computational complexity. We use regression based linear predictors and nonlinear neural predictors to build models of the system performance, power and energy consumption using the cross-layer events, hardware counters, and on-chip sensor data [6]. In addition, use of coupling parameters (a metric that quantifies the interactions between layers) helps to develop application and cross-layer interaction models for nominal and abnormal operations. We use the predictive and learning abilities of CPSoC to improve autonomy in managing the system resources and assisting proactive resource utilization in the run-time system [6].

### IV. CPSOC APPLICATIONS AND USE CASES

We demonstrate the applicability of CPSoC using several examples in [6]. Here we illustrate one such use case for accurate run-time power and temperature estimation and prediction using noisy thermal sensors placed at the suitable locations in the CPSoC fabric.

#### A. Virtual Run-time Power Sensing of Subsystems Using Noisy Thermal Sensors

This scenario illustrates the virtual sensing capability of CPSoC in jointly estimating and predicting the run-time transient power consumption and accurate temperature of each subsystem unit as well as accurate temperatures from noisy temperature sensors readings using the observe-decide-act (ODA) paradigm. The virtual approach (Fig.3(a)) combines a sensor-network-on-chip (sNoC) and a robust Kalman filter [14] to enable in-situ, on-the-fly run-time estimation of the power and temperature of each block/unit from on-chip noisy thermal measurements. Unlike traditional MPSoCs, the specialized sensor network (Fig.3(b)) can coexist independently or combined with the core-to-core communication network (cNoC) as shown in Fig.3(c). Such an architecture decouples the sensing and computation concerns and allows flexibility to independently perform on-chip sensing without interfering or burdening the core-to-core computation network.

Temperature values at different locations on the die depend on various factors such as power consumptions of functional units, layout of the chip and the package characteristics. The differential equations describing the heat flow have a form dual to that of electrical current, represented using lumped values of thermal R and Cs, and form the basis for commonly used micro-architectural thermal models in state space form [15][16].

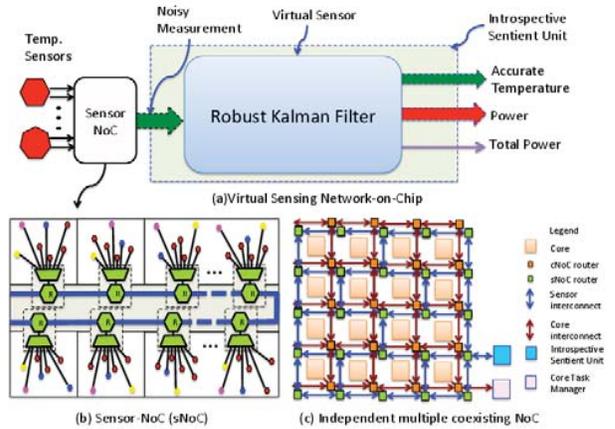


Figure 3. (a) Virtual Sensor Network-on-Chip Architecture (b) Sensor NoC (sNoC) (c) Independent multiple coexisting NoCs in CPSoC.

Virtual sensing of the run-time transient power requires the thermal model which represents the relation between subsystem power and the temperature. However, to address the emerging problem of semiconductor process variations in deep sub-micron technologies and sensor noise [17], the processor thermal dynamics is augmented with the process and measurement noise in the standard LTI model as:

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}_k \mathbf{x}_k + \mathbf{E}_k \mathbf{d}_k + \mathbf{w}_k \\ \mathbf{y}_k &= \mathbf{H}_k \mathbf{x}_k + \eta_k \end{aligned} \quad (1)$$

where  $\mathbf{x}_k \in \mathbb{R}^n$  are the system states (i.e., each block's temperature),  $\mathbf{d}_k \in \mathbb{R}^p$  are the unknown inputs (i.e., each block's power),  $\mathbf{y}_k \in \mathbb{R}^m$  are the measurements (i.e., the temperature sensor measurement),  $\mathbf{A}_k, \mathbf{E}_k, \mathbf{H}_k$  are system matrices of appropriate dimensions. The process noise  $\mathbf{w}_k$  and measurement noise  $\eta_k$  are assumed to be mutually uncorrelated, zero-mean, white random signals with known covariance matrices,  $\mathbf{Q}_k = \mathbf{E}[\mathbf{w}_k \mathbf{w}_k^T]$  and  $\mathbf{R}_k = \mathbf{E}[\eta_k \eta_k^T]$  respectively.

To effectively construct the virtual sensing mechanism for the variability and noise corrupted dynamic system in (1), we use an optimal Kalman filter to provide robust estimates. The objective of the Kalman filter is to jointly estimate the unknown power input  $\mathbf{d}_k$  as well as the temperature states  $\mathbf{x}_k$  from noisy temperature measurements in the presence of both process and measurement noise as described in Fig. 4. Robust Kalman filters [14] have been shown to provide unbiased estimates of the states and unknown inputs and guarantee global optimality and minimum variance of the estimates [14]. Consequently, virtual sensors constructed using such filters will provide the statistically best solution for the thermal and power estimation of the subsystems.

To validate our approach we created a CPSoC simulation platform called CPSoCSim [18]. We used the Alpha 31386 processor and its compilation tools that have been extensively used in earlier research work [15], [16]. We use the SPEC and PARSEC benchmarks and their corresponding power traces to generate the thermal profile using the Hotspot simulator [16]. We assume that the temperature of the blocks are measured with noisy sensors and are collected by the sNoC so that these can be processed to produce thermal and the power estimates at each subsystem unit of the processor. Figure 5 shows the actual temperature obtained from Hotspot [16] versus the temperature obtained from the virtual sensor. The estimation of the power of each unit and run-time tracking of total power consumed by the processor are shown in Fig. 6(a) and (b) respectively. Although the estimation error is a function of process and measurement noise, for typical scenarios the temperature and power estimate errors are less than 1% and 5% respectively. Note that no power sensors were used in the whole process of power estimation of the subsystems; results were generated indirectly by computational means using virtual sensing.

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**Algorithm: Virtual Sensing of Subsystem Power and Temperature**


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**Input:** Temperature sensor measurement from sensors  $y$ , Thermal state space model  $A_k, E_k, H_k, Q_k, R_k$   
**Output:** Subsystem Thermal Profiles,  $\hat{x}_k$ , and Power Profile,  $\hat{d}_k$ , Total Power,  $P_{total}$

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Perform the following every sampling step:

- 1) Initialize the values of  $\hat{x}_k, \hat{P}_k, A_k, E_k, H_k, Q_k, R_k$
  - 2) Robust Two-Stage Kalman Filter (RTSKF):
    - a)  $\hat{x}_{k|k-1} = A_k \hat{x}_{k|k-1}$
    - b)  $\hat{P}_{k|k-1} = A_{k-1} \hat{P}_{k-1|k-1} A_{k-1}^T + Q_{k-1}$
    - c)  $C_k = H_k \hat{P}_{k|k-1} H_k^T + R_k$
    - d)  $P_{k|k}^d = \{E_{k-1}^T H_k^T C_k^{-1} H_k E_{k-1}\}^{-1}$
    - e)  $K_{k|k}^d = P_{k|k}^d E_{k-1}^T H_k^T C_k^{-1}$
    - f)  $K_{k|k}^x = P_{k|k-1} H_k^T C_k^{-1}$
    - g)  $V_k = (I - K_{k|k}^x H_k) E_{k-1}$ ,  $I$  is identity matrix
    - h)  $\hat{d}_{k|k} = K_{k|k}^d (y_k - H_k \hat{x}_{k|k-1})$
    - i)  $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_{k|k}^x (y_k - H_k \hat{x}_{k|k-1})$
    - j)  $\hat{P}_{k|k} = P_{k|k} + V_k P_{k|k} V_k^T$
    - k)  $P_{k|k}^x = (I - K_{k|k}^x H_k) P_{k|k-1}$
    - l)  $\hat{x}_{k|k} = \hat{x}_{k|k-1} + V_k \hat{d}_{k|k}$
  - 3) Output the estimates: Power Estimates,  $\hat{d}$ ; Total Power,  $P_{total}$ ; Temperature Estimates,  $\hat{x}$
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Figure 4. Virtual Sensing of Core and Subsystem Temperature and Power.

The overall overhead of the CPSoC considering 1000 sensors (consisting of 5 types), the sNoC and the ISU is within 7.3150 % of the area and 0.6476 % of the power budget of an equivalent 16-core ARM Cortex A9 platform. Using virtual sensing of power the overall overhead is further reduced to 1.6834% of the area and 0.2529% of the power budget of the 16-core platform [6].

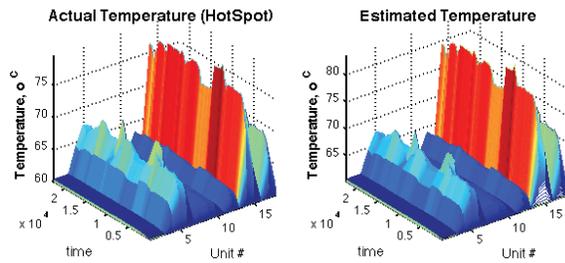


Figure 5. Run-time subsystem temperature estimation.

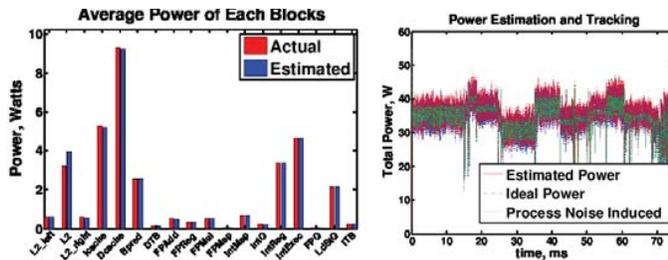


Figure 6. (a) Power estimation of subsystem units (b) Run-time total power estimation and tracking.

### B. Improving System QoS through Cross-Layer Adaptation

On-chip self-awareness with cross-layer virtual and physical sensing and actuation is a key enabling technology for efficient use of heterogeneous architectures, and applications with guaranteed runtime system goals and QoS (performance, reliability, power, thermal behavior) in a highly dynamic environment. Our Technical Report [6] contains several sample applications where self-awareness is used to improve energy efficiency, increase system lifetime by reducing aging effects and improve system performance under thermal constraints. For instance, we show that cross-layer virtual sensing and actuation can improve the sensing accuracy and reduce the

sensing overhead of thermal estimation by an order of magnitude [6]. In another example we show how virtual sensing enables an adaptive scheduler (an actuation mechanism) to exploit heterogeneous architectures for energy efficiency; our experimental result shows over a 50 % improvement in energy efficiency for a quad-core system with much higher gains expected for larger systems. We also demonstrate a 4-year improvement in lifetime for a 20-core heterogeneous CPSoC compared to a traditional (area and power equivalent) homogenous MPSoC that has an average 28-year lifetime. We are currently investigating more aggressive cross layer sensing and actuation mechanisms to improve system resilience and energy efficiency using a FPGA emulation and prototyping platform [18].

## V. CONCLUSION

In this paper we presented CPSoC, a sensor-actuator-rich MPSoC platform that deploys the computation-communication-control co-design of CPS together with cross-layer adaptations to achieve multiple design objectives. The CPSoC paradigm enables self-awareness (i.e., the ability of the system to observe it's own internal and external behaviors such that it is capable of making judicious decisions) and (selective or opportunistic) adaptation using the concepts of cross-layer physical and virtual sensing and actuations. In [6] we illustrate CPSoC's potential for self-awareness and cross-layer adaptations using several examples, and in this paper we present the specific instance of estimating power and temperature accurately with low overhead at runtime.

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