Optimal Design for Symbiotic Wearable Wireless Sensors

Priyanka Bagade, Ayan Banerjee and Sandeep K. S. Gupta
CIDSE, Arizona State University, Tempe, Arizona
Email: {pbagade, abanerj3, sandeep.gupta}@asu.edu

***Abstract*—Sensors aesthetically embedded in accessories such as jewelry, piercings or contact lenses are being proposed recently. These symbiotic wearable wireless sensors are envisioned to operate on scarce harvested energy resources from the human body. In addition to the hardware and software constraints arising from the form-factor and low energy operations, there are safety requirements such as avoidance of physical injury. The design implications of these requirements are non-intuitive and may involve estimation of human physiological dynamics. The physical impact of a sensor operation can be controlled by appropriate design of multiple sensor components such as processor, radio, and optimization of data algorithm. For example, the risk of thermal injury to tissue can be reduced by limiting the sensing frequency, the computation power, and the radio duty cycle of body worn sensor. Hence, it is a challenging task to trace back a cause of a physical impact to hardware and software design decisions in a sensor. This paper proposes a novel non-linear optimization framework to consider safety and sustainability requirements that depend on the human physiology and derive system level design parameters of a sensor. We demonstrate our methodology using three case studies: a) continuously monitoring ECG sensor sustained by body heat, b) thermally safe network of implanted sensors, and c) infusion pump control algorithm to avoid hypo-glycemia.**

Keywords*—*Body sensor network, safety, sustainability, wearable sensor design.

I. Introduction

Advances in flexible ultra low power electronics have resulted in prototypes of new age non-invasive symbiotic sensors [1] that can be embedded in accessories such as contact lenses [2] and body piercings [3]. They are envisioned to operate using energy scavenged from the human body. Such sensors when supplemented with continuous communication capabilities can be used for non-invasive "smart" behavioral monitoring such as sleep monitoring in babies [4] or providing visual feedback [2]. Enabling continuous communication is often not feasible since the radio power consumption quickly overwhelms the limited power storage of a sensor [5]. Researchers have considered several hardware as well as software designs for continuous monitoring and communication in sensors to satisfy the form-factor or energy consumption barriers [5]–[7]. However, a significant issue for wearable sensors, which has received limited focus, is their interaction with the human body that can have serious implications on the sensor hardware and software design. For example, stabilizing the infusion rate of an autonomous infusion pump may require a specific sampling frequency of the glucose sensor. This sampling frequency is governed by a function of the diffusion dynamics inside a human body. In another example, an energy sustainable duty cycle of the communication radio may cause thermal injury when the sensor is installed in sensitive areas such as the cornea [8]. Evaluating the impact of a certain hardware or software design decision on the human body can be accurately modeled using complex differential equations and solved using state of the art simulators. In contrast, this paper considers the reverse problem of finding the implications of physiology dependent system requirements such as user safety on the sensor design aspects. This is a far more challenging problem since the design implications can pervade over several system components.

As an example, if we consider a sensor embedded in a contact lens, we will have to consider its thermal effects on the human eye. This is because the human eye has less blood perfusion and hence is more prone to thermal injury. A high thermal impact can be caused by several sensor components including high sensing frequency, high communication power, and high data rate. A thermal safety requirement can be imposed that requires the temperature of the cornea to be below 37.8 °C. Such a requirement can have impact on frequency of sensing, radio duty cycle and computation workload. Further, these constraints are not static, vary with sensor location and material properties.

In another example of autonomous insulin infusion pumps, embedded sensors and actuators may be directly involved in controlling the human physiology. The insulin pump controller samples blood glucose concentration from a remote glucosemeter through the wireless channel and computes the insulin infusion input that will stabilize the blood glucose level. The insulin glucose interaction is often modeled using non-linear spatio-temporal differential equations [9]. The stability of the dynamics depends on the sampling rate of the glucosemeter, random extra infusion bolus requests by the user, and also the wireless channel characteristics. Thus, the requirement to stabilize the blood glucose level within a certain value can have implications on several components of the autonomous pump. *In this*

The research is funded by NSF grants CNS-0831544 & IIS-116385. The authors are thankful to OSEL group at FDA for providing us insights on medical device safety issues.

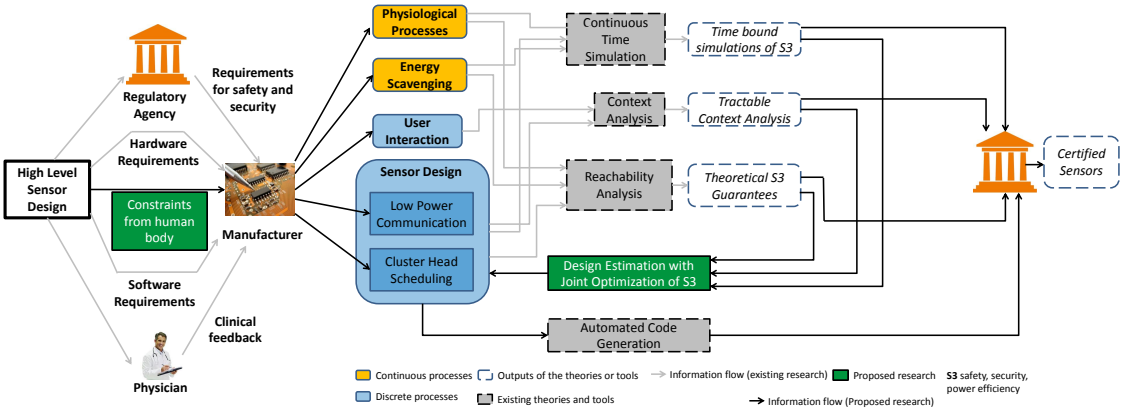

Figure 1: Proposed system level design optimization framework.

paper, we hypothesize that derivation of the optimal sensor design that meets safety or energy sustainability requirements will need a parameterized optimization of the interactions between the sensor and human physiological dynamics.

Design of a sensor can involve several aspects ranging from chip manufacturing to system level configurations such as determining the optimal sensing frequency. However, in this paper, we show case studies where we determine system level configurations of the sensor network. These configurations include, power consumption of different sensor components e.g., processor, sensing, and communication, frequency of sensing, data transmission rate, parameters of algorithms, and configurations of routing protocols.

A. Proposed Framework

In our proposed framework (Figure 1), along with the hardware and software constraints imposed by the technology, the manufacturer should also consider requirements coming from the human body dynamics. These requirements are typically imposed by regulatory agencies or physicians and may not be readily converted to hardware and software constraints. *To this effect, the paper proposes techniques to objectively convert requirements from human body dynamics to hardware and software constraints.* Given these constraints, the manufacturer should develop a high level sensor design. The design can then be evaluated with respect to the requirements using tools (Figure 1) that can accurately model the interactions between sensor operation and human physiology. Typically three types of interactions are considered: a) interaction of the sensor with the human physiology, b) interaction of the sensor with the random human user behavior, such as user inputs, that lead to changes in context of the sensor operation, and c) interaction of the sensor with the human body parts for harvesting energy. We use tools such as BAND-AiDe [10] and Simulink [11] that can simulate continuous time models of interaction between sensors and the human body, and context simulation tools [12] that can consider effects of user inputs on the sensor operation. Apart from simulation tools, there are several formal approaches to analyze a sensor design with respect to requirements. There are hybrid automata based solutions [13], which are limited to analyze time based systems and spatio-temporal hybrid automata [9] for spatio-temporal interactions. TempLab [14] considers the effect of environment temperature on the clock drift, the battery discharge rate, and the wireless link quality of a wireless sensor networks. If the sensor network design is verified to satisfy requirements using the above mentioned tools the manufacturer can use automated code generators to develop a prototype. In this regard, several automated code generators, such as VipTOS [15], RaPTEX [16], and Health-Dev [17], which take verified sensor design and generate sensor code, can be used. However, all these techniques can only be used to evaluate an already existing sensor design. The proposed optimization framework uses the existing simulators to quantify the interaction between sensor and the human body, and evaluate the safety and sustainability requirements as objective functions. It then finds the optimal system level design parameters that minimize the objective. We test our optimization framework by determining system level configurations of wearable sensors and using experiments to verify that the implementation meets the requirements satisfied by the design. We have considered commercially available sensors including TelosB and Shimmer 2r as hardware testbeds and use the Health-Dev tool [17] to generate code from the optimized design. We use our optimization framework to derive thermally safe leader change sequence for implanted sensor clusters and an infusion control algorithm to avoid hypoglycemia.

II. System Model

In body sensor networks, various sensors are worn on the human body to monitor different physiological signals, e.g. the heart rate, the blood pressure, and the

glucose level. These symbiotic sensors are embedded in accessories such as bracelets, anklets, piercings, and contact lenses. Figure 2 shows the network of such sensors communicating with smartphone. One of the sensors in the network shown in Figure 2 is recently prototyped by Google Inc. It is a contact lens which monitors user's blood glucose level [2] from tears. The requirements for continuous monitoring and sustainable operation introduce various sensor design challenges, such as a) providing continuous monitoring and data transmission capability, since it increases the power requirements of the sensors, b) safety of the human body, so that operation of the sensors does not cause physical injury to sensitive parts, such as thermal injury [10], and c) designing on-chip energy harvesting and storage devices, that can store enough power to sustain the continuous monitoring and possibly power the alert display module. On top of this, the regulatory requirements of maintaining data privacy adds an immense power and form-factor overhead on the sensor design.

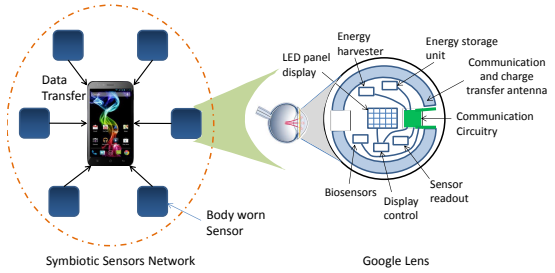

Figure 2: **State of the art in symbiotic sensor networks.**

A. *Motivating Examples*

Single sensor thermal safety: Thermal effects of a sensor on the human body follows a complex pattern and varies with the location and placement of the sensor. Sensors worn on the arm or on the chest, where the skin is not very sensitive to the heat energy, for short periods of time does not cause severe heat related problems. Sensors such as Shimmer, TelosB, with power consumption around 50 mW, cause negligible temperature rise in the human body ($\approx$ 0.01 °C) for a prolong operating time of 24 - 48 hours [5]. Symbiotic sensors on the other hand will have a power cap of 5 µW [8], but can have a higher thermal effect due to their location. We conducted a simulation study that shows a non-intuitive result as depicted in Figure 3. The skin temperature rise of a sensor with 1 mW power dissipation installed on the cornea is greater than that of a sensor with 50 mW power worn on the human arm for 24 hrs by almost 0.2 °C. Another interesting fact is that the reduction of sensor power does not significantly change the temperature rise. As shown in Figure 3, if power of the sensor is reduced to 5 µW [8] from 1 mW, the skin temperature reduces only by 0.01 °C. This result is due to the fact that the average temperature rise of the

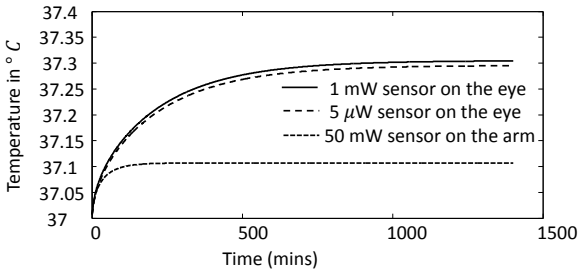

Figure 3: **Skin temperature rise depending on sensor location.**

human tissue around a sensor is not only a function of the power consumption of the sensor, the frequency of sensing, the data transmission rate but is also a function of the blood perfusion rate and hence varies based on the location of installation.

Networked Infusion Pump: In a networked autonomous infusion pump, a controller wirelessly samples the blood glucose levels from a glucose meter and computes the future infusion rate to stabilize blood glucose concentration in the human body. The interaction between insulin and glucose can be modeled as the spatio-temporal [18].

$$\frac{\partial d}{\partial t} = \bigtriangledown(D \bigtriangledown d) + \Gamma(d_B(t) - d) - \lambda d, \quad (1)$$

where $d(x,t)$ is the tissue drug concentration at time t and distance x from the infusion site, D is the diffusion coefficient of the blood, Γ is the blood to tissue drug transfer coefficient, $d_B(t)$ is the prescribed infusion rate at time t, and λ is the drug decay coefficient. The design of the controller involves finding five parameters, the optimal sampling rate of glucose sensor, infusion change or increment step by which the controller increases infusion, allowable bolus rate, the set point $d_B(t)$, and the delay in taking control decisions.

III. Problem Formulation

The principal research problem that we seek to answer in this paper is -

Given a set of design requirements expressed in the form of a set of favorable states, find a sensor design that always keeps the system in one of the favorable states.

Optimization approach: We frame the problem of finding the sensor design that satisfies regulatory requirements in an optimization framework. Let us consider a contact lens glucose sensor placed on the retina which consumes P_s power for sensing, P_c for data transmission, P_{sec} for executing security protocol. The sensor has an energy storage device of capacity B_c and its stored power at time t is denoted by $P_b(t)$. The energy available from the scavenging source is denoted by $E(t)$ at time t. There will be constraints on the frequency at which the sensor can sense and communicate data. Let us consider that the sensing frequency is f_s and the communication frequency is f_c. The aim is to determine P_s, P_c, P_{sec},

B_c, f_s and f_c from an optimization formulation that minimizes the temperature rise of the human body part and also never depletes the storage device.

Let us consider that the specific absorption rate of the tissue is *SAR*, which is directly proportional to the radio power and inversely proportional to the square of the distance between the sensor and the point at which temperature is to be calculated. The change in temperature of the tissue is represented using Penne's bioheat equation [19] as follows,

$$\rho C_p \frac{dT}{dt} = K \bigtriangledown^2 T - b(T - T_b) + \rho \mathrm{SAR} + P_{avg}, \tag{2}$$

where ρ is the mass density, C_p is the specific heat, K is the thermal conductance, and T is the temperature of the body part, A is the surface area of contact with the device, T_r is its temperature, b is the blood perfusion constant, T_b is the blood temperature, and P_{avg} is the average power required by the sensor.

The Penne's bioheat equation can be written as a temporal differential equation by discretizing it over $N \times N$ space grid. It is discretized over time and space using the finite difference time domain(FDTD) technique [19].

At grid points (i, j), the temperature $T(i, j)$ is:

$$\begin{aligned} \frac{dT(i,j)}{dt} &= \left[-\tfrac{(b\delta^2+4K)}{\rho C_p \delta^2}\right] T(i,j) + \tfrac{SAR}{C_p} + \tfrac{b}{\rho C_p} T_b + \tfrac{P_{avg}}{\rho C_p} \\ &+ \tfrac{K}{\rho C_p \delta^2}[T(i+1,j) + T(i,j+1) + T(i-1,j) \\ &+ T(i,j-1)]. \end{aligned} \tag{3}$$

If we consider $\boldsymbol{T}$ to be a vector consisting of the temperatures at each grid point, then Equation 3 is analogous to Equation 4, which is in the form of linear time invariant differential equation.

$$\dot{\boldsymbol{T}} = A\boldsymbol{T} + B, \tag{4}$$

where, matrix A will have dimensions $N^2 \times N^2$ and its each row will be as,

$$A = \begin{array}{c} \\ (\cdots \end{array} \begin{array}{ccccccccc} \cdots & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 & X_7 & \cdots \\ \cdots & \alpha & \cdots & \alpha & \beta & \alpha & \cdots & \alpha & \cdots) \end{array} \tag{5}$$

where, $\alpha = \frac{K}{\rho C_p \delta^2}$, $\beta = -\frac{(b\delta^2+4K)}{\rho C_p \delta^2}$, $X_1 = N(j-1)+i$, $X_2 = N-2$ zeros, $X_3 = N(j+1)+i$, $X_4 = Nj+i$, $X_5 = Nj+(i-1)$, $X_6 = N-2$ zeros, $X_7 = Nj+(i+1)$. The dotted elements of matrix A are all zero. The computed matrix B of dimension $N^2 \times 1$ is as follows,

$$B = \begin{array}{c} 1 \\ \vdots \\ N^2 \end{array} \begin{array}{c} 1 \\ \left(\begin{array}{c} \frac{SAR}{C_p} + \frac{b}{\rho C_p} T_b + \frac{P_{avg}}{\rho C_p} \\ \vdots \\ \frac{SAR}{C_p} + \frac{b}{\rho C_p} T_b + \frac{P_{avg}}{\rho C_p} \end{array} \right). \end{array} \tag{6}$$

The solution to Equation 4 is a non linear function of time given by,

$$\boldsymbol{T}(t) = e^{A(t-t_0)}\boldsymbol{T}(0) + e^{At}A^{-1}(e^{At} - e^{At_0})B, \tag{7}$$

where t_0 is the starting time.

The average power consumption of the sensor over a time τ can be obtained using Equation 8,

$$P_{avg} = (P_s f_s + (P_c + P_{sec}) f_c). \tag{8}$$

Find $P_s, P_c, P_{sec}, f_s, f_c,$ and B_c that minimizes
$abs(\varepsilon - max(\boldsymbol{T}(t) - \boldsymbol{T}(0)))\forall t \in [t_0 \ldots \tau]$
such that
[Penne's Equation] $, \forall t : \boldsymbol{T}(t) = e^{A(t-t_0)}\boldsymbol{T}(0) + e^{At}A^{-1}(e^{At} - e^{At_0})B,$
[Energy Neutrality], $(P_s f_s + (P_c + P_{sec}) f_c)\tau \leq \int_0^\tau E(t)dt,$
[Storage Constraint], $\forall t : P_b(t) \geq P_{avg},$
[Capacity Constraint], $\forall t : B_c \geq max\{P_s, P_c, P_{sec}\}.$

(11)

A principal requirement of the sensor to operate is the energy neutrality constraint. A system is energy neutral for a time τ if the storage device level remains unchanged after the execution, i.e., $P_b(0) = P_b(\tau)$. Thus, effectively all the power required for computation comes from scavenging sources (Equation 9),

$$(P_s f_s + (P_c + P_{sec}) f_c)(\tau - t_0) \leq \int_{t_0}^{\tau} E(t)dt. \tag{9}$$

The power from the scavenging sources are not directly provided to the sensor but has to be stored in a storage device. The storage device should have a capacity greater than the peak power consumption of the sensor. Also, the available charge at any time should be greater than the power requirements of the sensor,

$$P_b(t) \geq P_{avg} \text{ and } B_c \geq max\{P_s, P_c, P_{sec}\} \tag{10}$$

The aim of the optimization analysis is to find P_s, P_c, P_{sec}, B_c, f_s and f_c such the temperature rise is maximized without violating dangerous levels. In order to frame it as an optimization problem as shown in Equation 11, we have to convert the above requirement into an objective function. Let us assume that $\boldsymbol{T}$ should not increase by more than ε°C. In such a case, the objective function can be framed as minimization of the quantity, $abs(\varepsilon - max(\boldsymbol{T}(t) - \boldsymbol{T}(0)))\forall t \in [t_0 \ldots \tau]$, where τ is the final time.

For the energy scavenging unit the energy $E(t)$ can be given by the linear model $E(t) = \alpha(max(\boldsymbol{T}) - T_{amb})$, where α is the thermal resistance of the human body and T_{amb} is the ambient temperature.

IV. Validation

The optimization problem is solved in Matlab using *fmincon*, which starts with initial values of variables and minimizes the scalar function within the specified constraints. We show the usage of the optimization technique on three examples: a) single sensor operation, b) cluster head scheduling for implanted sensor networks, and c) designing infusion control algorithm.

A. Single sensor example

We use the problem formulation of Section III. The objective function of Equation 11 is used as a scalar function for *fmincon*. ε is considered as 0.1 °C. Energy sustainability of sensors are described by the battery constraints and energy neutrality constraints.

TABLE I: Power consumption of sensor query task.

Platform	Consumed Power	Time
TelosB	5.46 mW	500 ms
Imote2 (13 MHz)	156.15 mW	286 ms
BSN v3	6.586 mW	235 ms
SHIMMER 2R	7.145 mW	452.8 ms

TABLE II: Radio power consumption results with plaintext packets and encrypted packets.

Platform	Consumed Power Encrypted data(mW)	Consumed Power Plain data(mW)
TelosB	58.2	47.6
Imote2	209.4	198.3
BSN v3	70.7	59.7
SHIMMER 2R	72.4	60.1

We consider the initial values of design parameters as, sensing power $P_s = 7.1\mu$W, data transmission power $P_c = 50$ mW, power for executing security protocol $P_{sec} = 12$ mW, sampling frequency $f_s = 100$ Hz, and frequency of data transmission $f_c = 6/3600$ Hz. For forming the complete optimization problem, we set feasible design considerations for aforementioned parameters as $P_s = 5$ μW, $P_c = 1$ mW, $P_{sec} = 5$ mW, $f_s = 10$ Hz, and $f_c = 0.001$ Hz. These are minimum values of design parameters for currently available sensors. Using these values, we solved the optimization problem and obtained the optimized design parameters as $P_s = 8.3$ μW, $P_c = 61$ mW, $P_{sec} = 13.3$ mW, $f_s = 112$ Hz, and $f_c = 1/360$ Hz which satisfied all the constraints.

To implement and experimentally validate our optimization design, we have bench-marked commercially available sensing platforms TelosB, Shimmer, Imote2, and BSN v3. Table I enlists the power consumption of respective platform for sensing once. We measured sensing power and radio power while both plain data and encrypted data are being sent. Table II shows the bench-marking results for the radio power.

From Tables I and II, the Shimmer platform is the best match for our optimized power consumption constraint. Thus, we have used it for validation.

After obtaining optimal design for sensors and choosing testing platform as Shimmer, we need to develop software code for it with our optimized design. For code development, we have used the automated code generator, Health-Dev [17]. It takes requirements of wearable sensors in the form of models in Advanced Architectural Description language (AADL) and generates downloadable code for them. The automated code generation reduces manual implementation errors.

We input sampling frequency as 112 Hz, data transmission frequency of once every 6 mins, and choice of sensor as ECG sensor to Health-Dev [17]. Then, we have downloaded the generated code into Shimmer platform and wore it to measure ECG signal continuously for 12 hours. We conducted two sets of experiments: a) without any radio duty cycling and b) with the optimize sensing frequency and duty cycle. At the end of the testing period, we measured the energy required and rise in temperature of the body part. With no duty cycling and at a sampling rate of 250 Hz, the energy consumption was 432 J and the temperature rise was ($\leq$ 0.167 °C) on the arm. With the optimized design, the sensor consumed 11 J of energy and there was no measurable temperature rise. The power available from body heat was 9 J and we considered an energy storage unit with initial energy 4 J.

B. Networked implanted sensors

In this example, we consider a network of implanted sensors, which communicate in a cluster protocol. The implanted sensors form a cluster, where a cluster head collects all communication packets from the participating sensors and sends it out to a base station. Here, for each sensor, the sensing power P_s is fixed to 3 μW, communication power P_c is fixed at 5 μW and there is no security protocol, hence $P_{sec} = 0$. The sensing frequency is set at 10 Hz while the communication frequency is set at 0.5 Hz. Since the cluster head has to collect data from all other sensors, it has the most power consumption and the tissue around the cluster head is heated the most. To keep the temperature of the surrounding tissue within limits, the cluster head has to be frequently rotated. In this example, we find out the optimal cluster head rotation scheme that can keep the temperature within thresholds at different parts of the body.

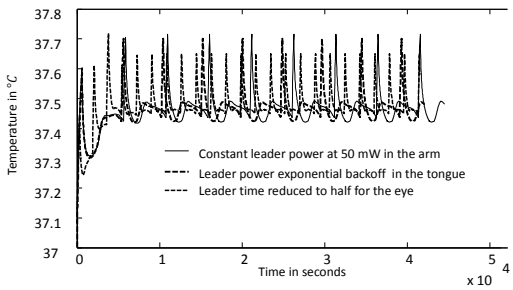

Figure 4: Cluster scheduling schemes for implanted sensors.

We observe that as the location within the body changes, different leader rotation schemes are needed to keep the temperature within thresholds as shown in Figure 4. In the arm where the blood perfusion is the lowest, the leader can be changed every 600 s to keep the temperature below 37.8 °C. However, for the same threshold a cluster in the tongue will have to have its leader power reduced to half, every time the temperature is greater than 37.6 °C in addition to changing its leader

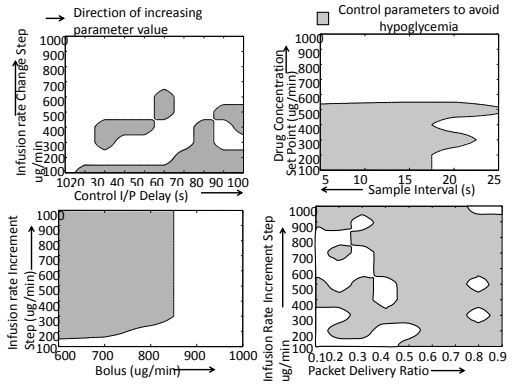

Figure 5: Infusion pump parameters for avoiding hypoglycemia.

every 600 s. If the implant is in the eye, the leader has to be changed every 300 s.

C. Designing infusion pump control algorithm

For the infusion pump case study, we consider a requirement that the drug concentration should not be above 1300 μg/min. Our aim is to derive the design parameters discussed in Section II-A such that this requirement is satisfied. In addition to the five design parameters, we also consider the packet delivery ratio as a measure of the wireless channel characteristics. Equation 1 is of the same form as the Penne's bioheat equation and hence can be solved using FDTD. The form of the objective function will thus be the same as that in Equation 11. Figure 5 shows the results of 10000 optimization runs. Since several local minimums are possible, we get a set of design parameters (within the gray bounded region) that satisfy the requirements.

V. Conclusion

This paper considers the problem of designing sensors to meet requirements that depend on human physiology, such as avoidance of physical injury. The cause of a physical impact of a sensor operation can span over several components of the sensor such as processor, radio, and algorithm parameters. Hence, it is a challenging task to trace back the cause of a particular physical impact on human body to hardware and software design decisions in a sensor. In this paper, we proposed a novel non-linear optimization framework to consider safety and sustainability requirements that depend on human physiology and derive system level design parameters of a sensing system. We used our optimization technique on three case studies including an ECG sensor run on bioheat energy, thermally stable network of implanted sensors, and an optimal infusion control algorithm design. We implemented the optimized design for the first case study on Shimmer 2r sensors and the measured power consumption and thermal impact were within the desired limits.

References

[1] A. Darwish and A. E. Hassanien, "Wearable and implantable wireless sensor network solutions for healthcare monitoring," *Sensors*, vol. 11, no. 6, pp. 5561–5595, 2011.

[2] Fox News, Google contact lenses. http://www.foxnews.com/tech/2014/01/16/google-announces-contact-lens-glucose-monitor/.

[3] "Sensor in piercings," http://gigaom.com/2013/11/28/how-tongue-piercings-and-sensors-can-help-paralyzed-people-drive-wheelchairs/, 2014.

[4] Intel, "Meet edison, intels tiny plan to power the next generation of wearables," http://readwrite.com/2014/01/07/meet-edison-intel-tiny-plan-to-power-the-next-generation-of-wearables, 2014.

[5] S. Nabar, A. Banerjee, S. K. S. Gupta, and R. Poovendran, "Evaluation of Body Sensor Network Platforms: A Design Space and Benchmarking Analysis," in *Wireless Health*, October 2010.

[6] ——, "GeM-REM: Generative model-driven resource efficient ecg monitoring in body sensor networks," in *Body Sensor Networks (BSN), Intl Conference on*, May 2011, pp. 1 –6.

[7] S. K. S. Gupta, T. Mukherjee, and K. K. Venkatasubramanian, *Body Area Networks: Safety, Security, and Sustainability*. Cambridge University Press, 2013.

[8] Y.-T. Liao, H. Yao, A. Lingley, B. Parviz, and B. Otis, "A 3- μ W cmos glucose sensor for wireless contact-lens tear glucose monitoring," *Solid-State Circuits, IEEE Journal of*, vol. 47, no. 1, pp. 335–344, Jan 2012.

[9] A. Banerjee and S. K. S. Gupta, "Spatio-temporal hybrid automata for safe cyber-physical systems: A medical case study," in *Intl Conf on Cyber-Physical Systems*, 2013.

[10] A. Banerjee, S. Kandula, T. Mukherjee, and S. K. S. Gupta, "BAND-AiDe: A tool for cyber-physical oriented analysis and design of body area networks and devices," *ACM Trans. on Embedded Computing Systems*, 2010.

[11] MATLAB, "Simulink," http://www.mathworks.com/.

[12] A. Banerjee and S. K. S. Gupta, "Your mobility can be injurious to your health: Analyzing pervasive health monitoring systems under dynamic context changes," in *Pervasive Computing and Communications, Intl Conf on*. IEEE, 2012, pp. 39–47.

[13] S. Coleri, M. Ergen, and T. J. Koo, "Lifetime analysis of a sensor network with hybrid automata modelling," in *WSNA '02: ACM Intl workshop on Wireless sensor networks and applications*. NY, USA: ACM, 2002, pp. 98–104.

[14] C. A. Boano, M. Zúñiga, J. Brown, U. Roedig, C. Keppitiyagama, and K. Römer, "Templab: a testbed infrastructure to study the impact of temperature on wireless sensor networks," in *Intl Symp on Information processing in sensor networks*. IEEE, 2014, pp. 95–106.

[15] E. Cheong, E. A. Lee, and Y. Zhao, "Viptos: a graphical development and simulation environment for tinyos-based wireless sensor networks," in *Intl Conf on Embedded networked sensor systems*, ser. SenSys. NY, USA: ACM, 2005, pp. 302–302.

[16] J. B. Lim, B. Jang, S. Yoon, M. L. Sichitiu, and A. G. Dean, "Raptex: Rapid prototyping tool for embedded communication systems," *ACM Trans. Sen. Netw.*, pp. 7:1–7:40, August 2010.

[17] A. Banerjee, S. Verma, P. Bagade, and S. K. S. Gupta, "Healthdev: Model based development pervasive health monitoring systems," in *Body Sensor Networks (BSN), Intl Conf*, May 2012, pp. 85–90.

[18] T. L. Jackson and H. M. Byrne, "A mathematical model to study the effects of drug resistance and vasculature on the response of solid tumors to chemotherapy," *Mathematical Biosciences*, vol. 164, no. 1, pp. 17 – 38, 2000.

[19] H. H. Pennes, "Analysis of tissue and arterial blood temperature in the resting human forearm," in *Journal of Applied Physiology*, vol. 1.1, 1948, pp. 93–122.