

Optimal Continuous Glucose Monitoring Sensor Calibration for Patients with Type 1 Diabetes

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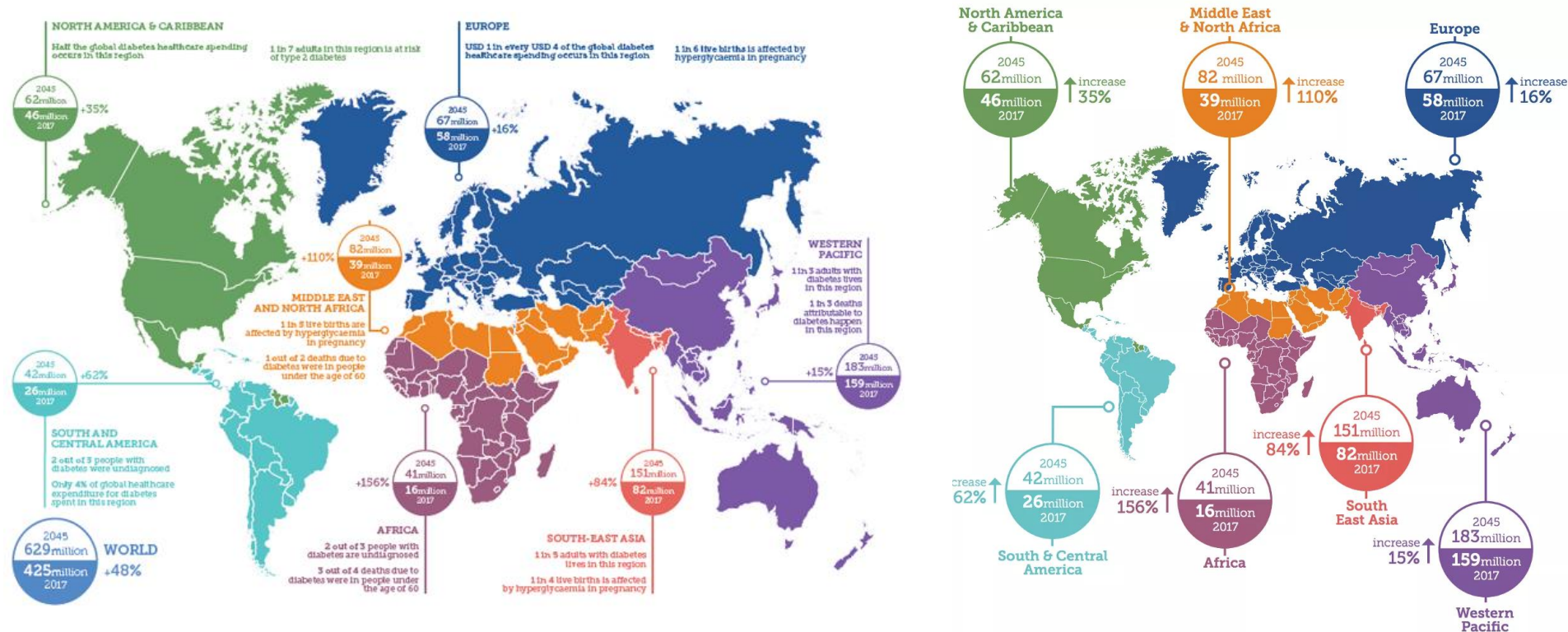
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1. Background



- Diabetes is one of the four major chronic diseases in the world with severe complications such as cardiovascular disease and chronic kidney disease.
- The World Health Organization (WHO) reports there are more than 400 million adults who are suffering from diabetes

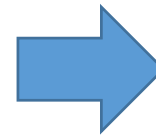


It is urgent to improve the blood glucose management technology for diabetic patients

2. Objective



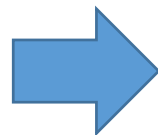
Blood Glucose Measuring Approach



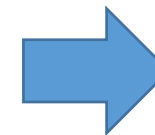
**Self Monitoring Blood Glucose(SMBG)
requires finger prick measurement**

Continuous Glucose Monitoring (CGM)

**Environmental
noise corruption**



**Periodic
calibration**



**Increase patient
discomfort**

Reducing calibration frequency with undiminished accuracy is of great importance

3. Introduction



Guerra et al, **IEEE Trans. Biomed. Eng.**, 2012.

Enhance the calibration signal and possibility to reduce finger prick frequency

F. Barcelo et al, **Diabetes Technol. Ther.**, 2012.

Considered plasma glucose as a static value by ignoring BG-IG dynamics

Acciaroli et al, **Diabetes Technol. Ther.**, 2016.

Reduced finger prick frequency but only valid for a limited time interval

Acciaroli et al, **IEEE Trans. Biomed. Eng.**, 2018.

Successfully reduced the finger prick frequency but deconvolution approach is complex

4. Framework



□ Calibration Model



Dexcom G4 Platinum Subcutaneous Sensor



Calibration Model

$$y_i(t) = [u_i(t) + b] \cdot s(t) + v(t)$$

BG-IG Model

$$\tau \frac{d}{dt} u_i(t) = -u_i(t) + u_b(t) + w(t)$$

Estimation Parameter

$$p = [s_2, s_3, b]$$

Sensitivity Model

$$s(t) = s_1 \alpha(t) + s_2 \beta(t) + s_3$$

Time Constant

$$\tau = \frac{1}{k_{02} + k_{12}}$$

4. Framework



□ Dynamic Blood Glucose Model and Discretization

$$\dot{u}_i(t) = -\frac{1}{\tau}u_i(t) + \frac{1}{\tau}u_b(t)$$

$$y_i(t) = s(t)u_i(t) + bs(t) + w(t)$$

Dynamic Blood Glucose Model



$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$y(t) = Cx(t) + Du(t)$$

Continuous Dynamic Blood Glucose Model

$$\begin{aligned} H(T) &= A^{-1} \int_0^T A e^{A\lambda} d\lambda B = A^{-1} e^{A\lambda} \Big|_{\lambda=0}^T B \\ &= A^{-1} (e^{AT} - I) B = (e^{AT} - I) B A^{-1} \\ G(T) &= e^{AT} \end{aligned}$$

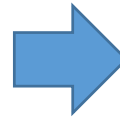
Discretization Model



$$x_{k+1} = Gx_k + Hu_{b,k} + w_k$$

$$y_k = C_k x_k + Du_{b,k} + v_k$$

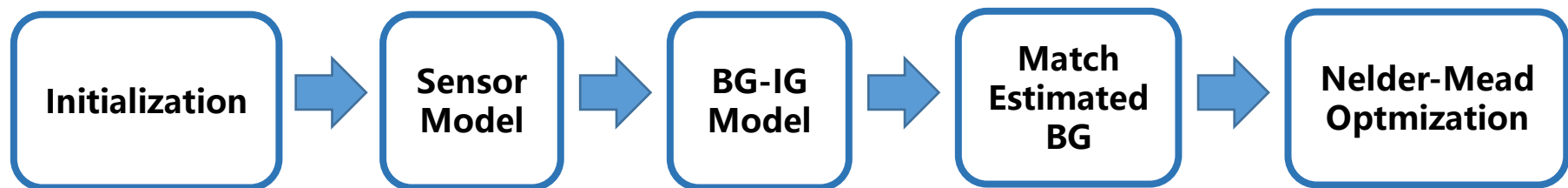
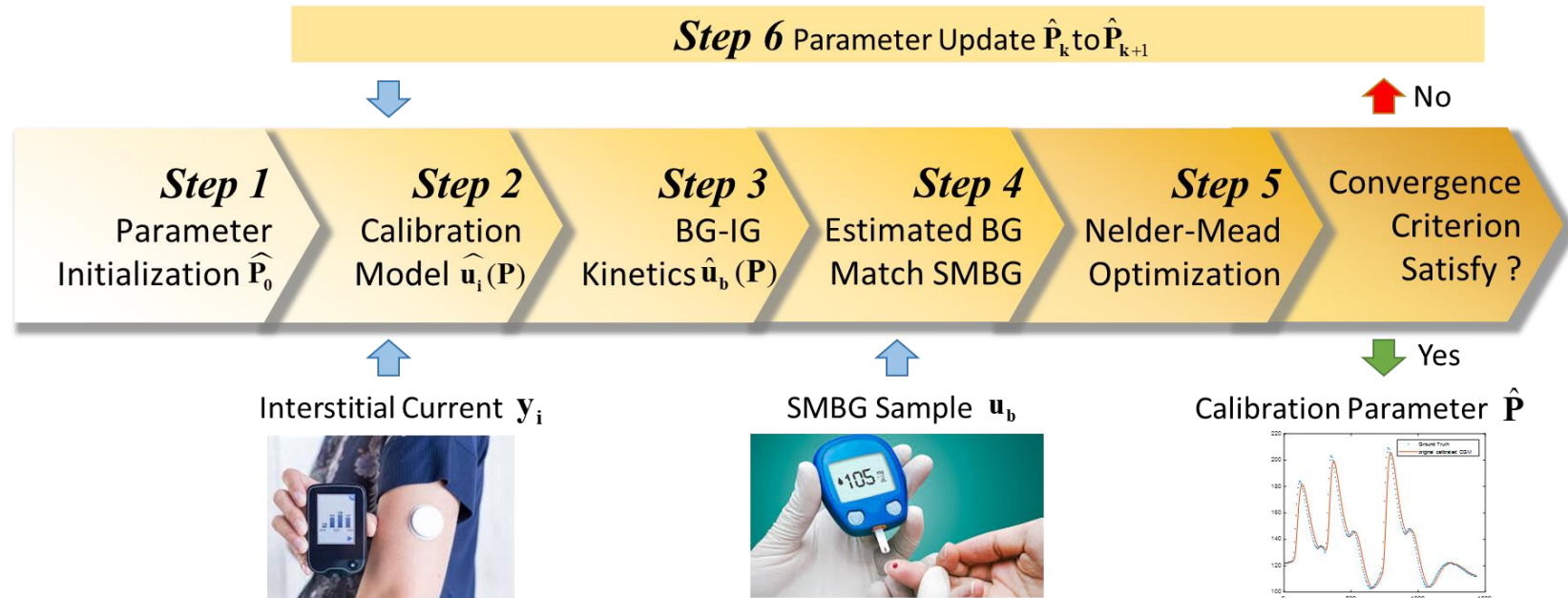
Discretized Dynamic Blood Glucose Model



4. Framework



Algorithm



□ Blood Glucose to Interstitial Glucose Model

Major Challenge

BG-IG model may indicate a complex time relation when given IG profiles inducted by electric current to infer corresponding BG value

Unknown Input Observer

Unknown Input Update: $\hat{u}_{b,k-1} = M_k (y_k - C_k \hat{x}_{k|k-1})$

Time Update: $\hat{x}_{k|k-1} = A \hat{x}_{k-1|k-1} \quad x_{k|k}^* = \hat{x}_{k|k-1} + B \hat{d}_{k-1}$

Measurement Update: $\hat{x}_{k|k} = x_{k|k}^* + K_k (y_k - c_k x_{k|k}^*)$

Yong et al, *Automatica*, 2016.

□ Theorem 1

When given state-space representation of glucose model and measurement information $\{y_1, y_2, \dots, y_k\}$, the estimate of unknown input $\hat{u}_{b,k}$ and state variable $x_{k+1|k+1}$ at time step k

$$\hat{u}_{b,k} = \frac{1}{C_{k+1}B} (y_{k+1} - C_{k+1} \frac{Ay_k}{C_k}) \quad x_{k|k} = \frac{y_k}{C_k}$$

□ Proof:

Base case: when $k=1$:

$$\hat{u}_{b,1} = M_2(y_2 - c_2 \hat{x}_{2|1}) = \frac{1}{C_2 B} (y_2 - C_2 \frac{Ay_1}{C_1}) \quad x_{2|2} = \hat{x}_{2|2}^* + K_2(y_2 - C_2 \hat{x}_{2|2}^*) = \frac{y_2}{C_2}$$

The theorem holds when $k=1$

Inductive step: from k to $k+1$

$$u_{b,k+1} = M_{k+1}(y_{k+1} - C_{k+2}x_{k+1|k}) = \frac{1}{C_{k+2}B} (y_{k+2} - C_{k+2} \frac{Ay_{k+1}}{C_{k+1}}) \quad x_{k+1|k+1} = x_{k+1|k+1}^* + K_{k+1}(y_{k+1} - C_{k+1}x_{k+1|k+1}^*) = \frac{y_{k+1}}{C_{k+1}}$$

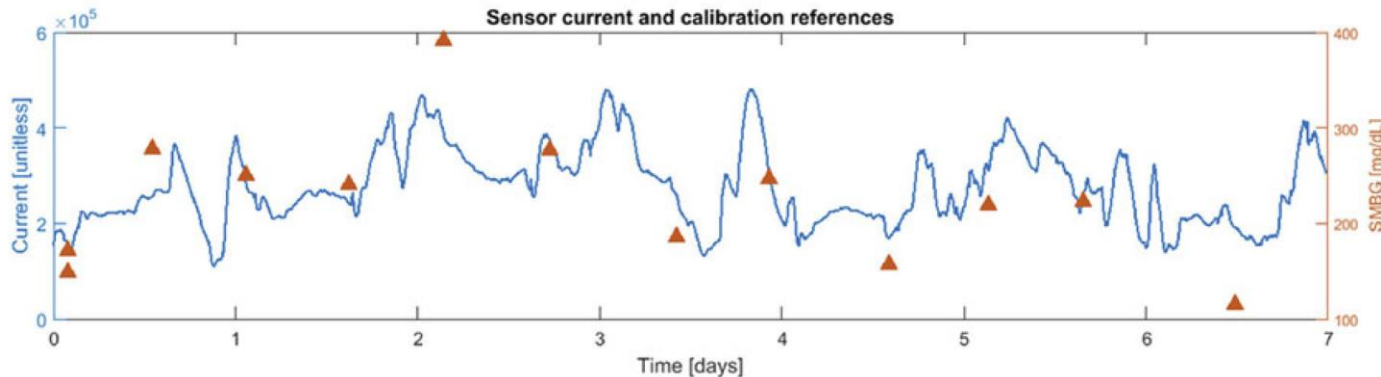
As a result, theorem 1 holds true.

Estimated glucose profile at time **k** **only correlates** with interstitial glucose profile at time **k** and **k+1**

□ Match estimated glucose profile

$$\hat{u}_{b,k}(p_k) = [\hat{u}_b(t_1, p_k), \hat{u}_b(t_2, p_k), \dots, \hat{u}_b(t_k, p_k)]^T$$

We match our estimated glucose profile with SMBG (self-monitoring blood glucose system) sampled patients blood glucose in time axis



□ Nelder-Mead simplex optimization

$$P = \arg \min_{p_i} \left\{ \frac{1}{N} \sum_{k=1}^N (u_{b,k} - u_{b,k}(p_i))^2 + \lambda p_i^T p_i \right\}$$

□ Evaluation metrics

Mean absolute relative deviation (MARD):

$$MARD = \frac{1}{n} \sum_{k=1}^n \frac{|z_k - x_k|}{x_k} \times 100\%$$

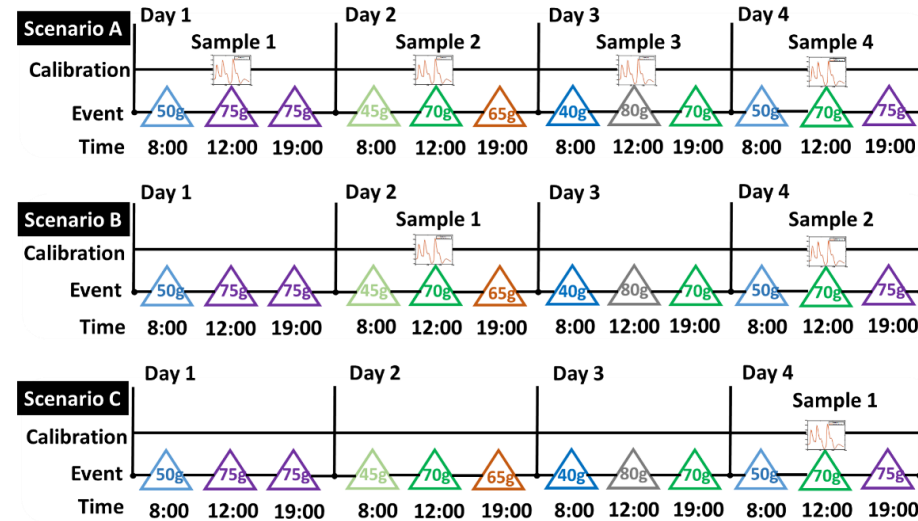
Percentage of accurate glucose estimators (PAGE):

$$d_k = \begin{cases} |x_k - z_k|, & \text{if } x_k \leq 80 \frac{mg}{dL} \\ \frac{|x_k - z_k|}{x_k}, & \text{if } x_k > 80 \frac{mg}{dL} \end{cases}$$

Clark error grid lying on "A" zone (CEGA-A):

The CEGA-A approach is used to assess the clinical significance of differences between the glucose measurement technique under test and the venous blood glucose reference measurements

□ Calibration Scenarios

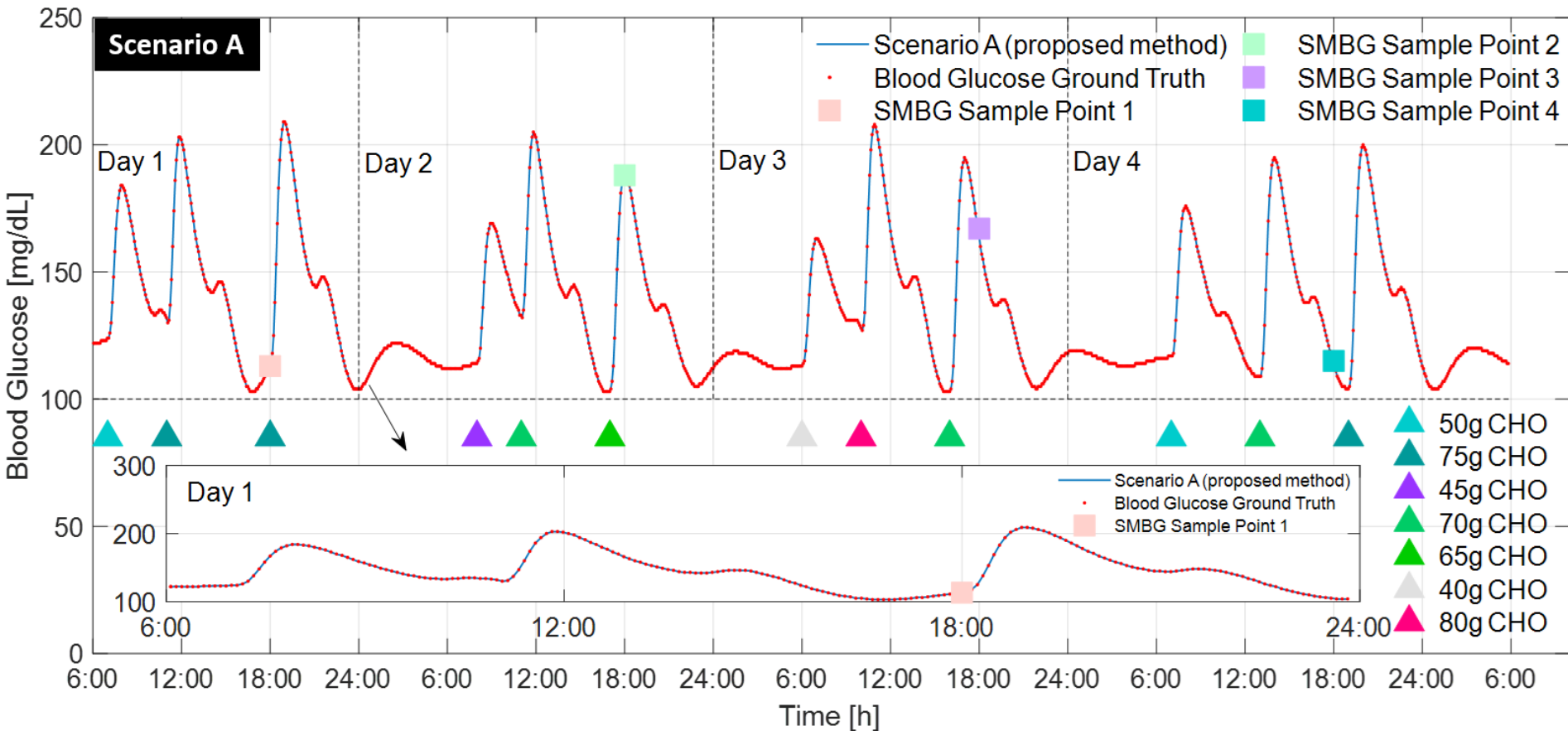


Scenario A: 1 cal/1 day
Scenario B: 1 cal/2 days
Scenario C: 1 cal/4 days

5. In Silico



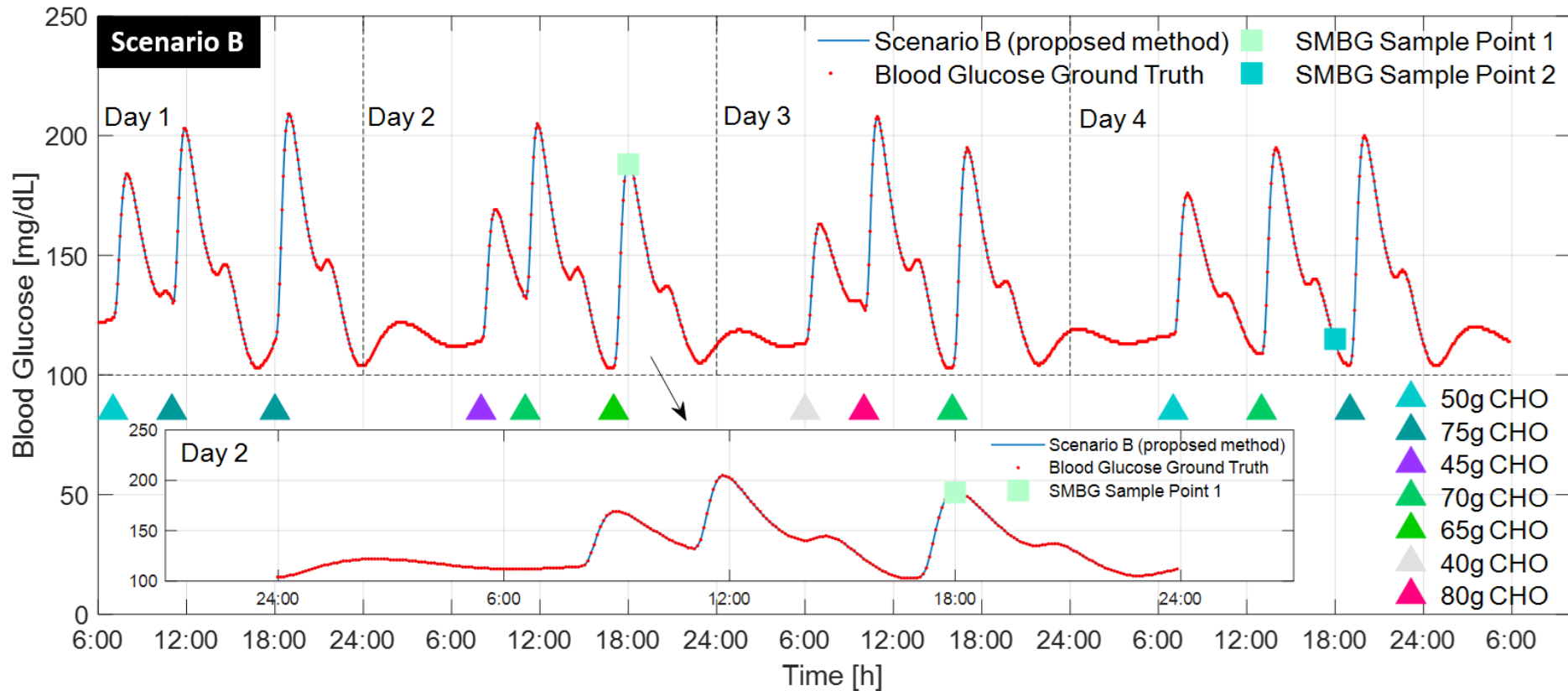
Scenario A: 1 cal/1 day



5. In Silico



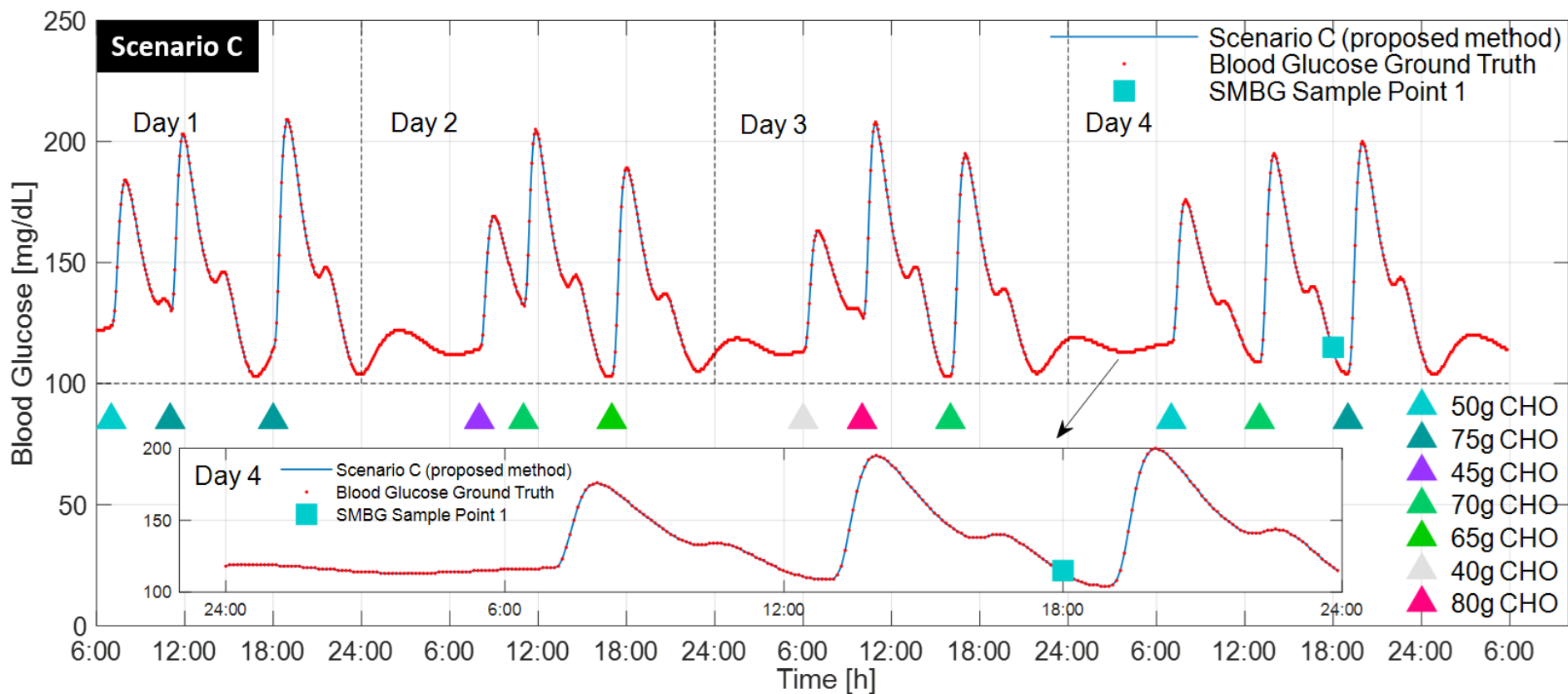
Scenario B: 1 cal/2 days



5. In Silico



Scenario C: 1 cal/4 days



□ Evaluation Metrics

| Evaluation Metrics | Original Calibration | Scenario A (1 cal/day) | Scenario B (2 cal/day) | Scenario C (3 cal/day) |
|--------------------|----------------------|------------------------|------------------------|------------------------|
| MARD (%) | 3.39 | 0.1 | 0.11 | 0.11 |
| PAGE (%) | 94.6 | 100 | 100 | 100 |
| CEGA-A (%) | 98.9 | 100 | 100 | 100 |

The calibration algorithm reaches satisfying frequency and accuracy



Thanks

