

A Simple and Straightforward Linear Approximation Model of Predicting the Glucose and HbA1C Values to Manage Type 2 Diabetes Based on GH-Method: Math-Physical Medicine (No. 472)

Gerald C Hsu

EclaireMD Foundation, USA

***Corresponding author**

Gerald C Hsu, EclaireMD Foundation, USA

Submitted: 16 July 2021; **Accepted:** 23 July 2021; **Published:** 11 Aug 2021

Citation: Gerald C Hsu (2021) A Simple and Straightforward Linear Approximation Model of Predicting the Glucose and HbA1C Values to Manage Type 2 Diabetes Based on GH-Method: Math-Physical Medicine (No. 472). *J App Mat Sci & Engg Res*, 5(2), 1-7.

Abstract

Based on research work over 6.5 years, the author summarized his work results into a set of simple and straightforward linear model to predict approximate, but accurate enough, sensor glucose and HbA1C values. It utilizes both of the linear elastic glucose theory (LEGT) from strength of engineering materials and the first-order interpolation perturbation theory (perturbation) from quantum mechanics to construct various PPG waveforms.

To start, he measures his weight in early morning, next he estimates his fasting plasma glucose (FPG) at his wakeup moment, then approximates his breakfast post-prandial plasma glucose (PPG) at 0-minute time instant, and finally applies either LEGT model or perturbation model to construct his daily PPG waveform over a three-hours timeframe. Based on the estimated FPG value and three PPG values, he can then assess his daily average sensor glucose (eAG) and HbA1C (A1C) value on that particular day.

In summary, this described linear approximation model of type 2 diabetes (T2D) control is contingent on various findings in each stage of his research work. By using observation, analysis, induction, verification, and simplification, he gradually discovers the evolutionary steps of application of his GH-method: math-physical medicine (MPM) methodology on diabetes.

In this particular article, he utilized his own CGM sensor-based glucose data from 5/5/2018 to 7/5/2021 to illustrate and verify his developed simple linear approximation model.

There are five key steps in this simple linear model:

1. weight to FPG in 2015 & 2016,
2. FPG to initial PPG in 2017,
3. eAG from both FPG and PPG in 2018,
4. construction of PPG waveforms in 2019 & 2020,
5. sensor-based A1C calculation in 2021.

Among these 5 steps, the fourth step of the construction of PPG waveform is the most sophisticated one.

The following listed data with their embedded formulas or mathematical methods recaps his finding results:

Weight = 171 lbs (*63%)

FPG = 107 mg/dL (+9 mg/dL or +18 mg/dL)

to get the **initial of breakfast PPG**

= 116 mg/dL

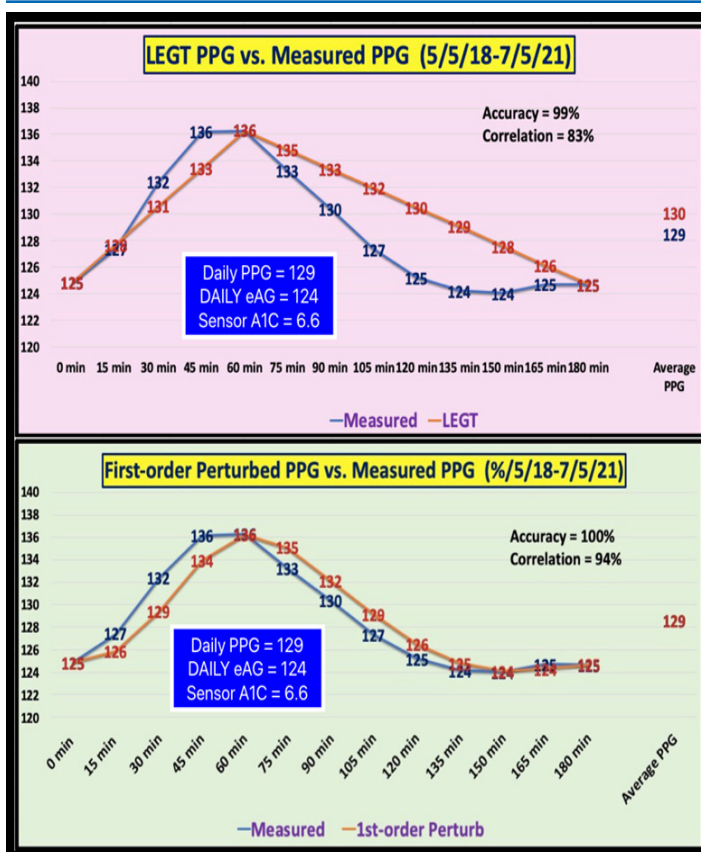
or the **Initial of daily PPG**

= 125 mg/dL

via LEGT model, to get **average PPG = 130 mg/dL (99% Accuracy)**

via Perturbation, to get **average PPG = 129 mg/dL (100% Accuracy)**

This simple linear approximation model has achieved an extremely high 99%-100% prediction accuracy with a remarkably high 83%-94% correlation coefficient (R) that is the waveform shape similarity between measured PPG and approximated PPG.



Introduction

Based on research work over 6.5 years, the author summarized his work results into a set of simple and straightforward linear model to predict approximate, but accurate enough, sensor glucose and HbA1C values. It utilizes both of the linear elastic glucose theory (LEGT) from strength of engineering materials and the first-order interpolation perturbation theory (perturbation) from quantum mechanics to construct various PPG waveforms.

To start, he measures his weight in early morning, next he estimates his fasting plasma glucose (FPG) at his wakeup moment, then approximates his breakfast post-prandial plasma glucose (PPG) at 0-minute time instant, and finally applies either LEGT model or perturbation model to construct his daily PPG waveform over a three-hours timeframe. Based on the estimated FPG value and three PPG values, he can then assess his daily average sensor glucose (eAG) and HbA1C (A1C) value on that particular day.

Methods

The author has chosen not to repeat all of the details regarding his applied methods as described in other papers. Instead, he outlines a few important equations, formulas, or conditions in this article.

MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from the published 400+ medical papers.

The first paper, No. 386, describes his MPM methodology in a general conceptual format. The second paper, No. 387, outlines

the history of his personalized diabetes research, various application tools, and the differences between biochemical medicine (BCM) approach versus the MPM approach. The third paper, No. 397, depicts a general flow diagram containing ~10 key MPM research methods and different tools.

All of listed papers in the section of references are from his written and published medical research papers.

The Author's Case of Diabetes

The author has been a severe type 2 diabetes patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time. By 2010, he still weighed 198 lb. (BMI 29.2) with an average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached to 1161 and albumin-creatinine ratio (ACR) at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and his future high risk of dying from his severe diabetic complications. Other than cerebrovascular disease (stroke), he has suffered most of known diabetic complications, including both macrovascular complications and microvascular complications.

In 2010, he decided to self-study endocrinology, diabetes, and food nutrition. During 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, PPG, FPG, and A1C. As a result, from using his developed mathematical metabolism index (MI) model and the four prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg, BMI 32.5) to 176 lbs. (89 kg, BMI 26), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger glucose reading from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications since 12/8/2015.

In 2017, he has achieved excellent results on all fronts, especially glucose control. However, during the pre-COVID period of 2018 and 2019, he traveled to approximately 50+ international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control, through dinning out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolism impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control was affected during this two-year period.

During 2020 with the special COVID-19 quarantined lifestyle, not only has he published approximately 400 medical papers in 100+ journals, but he has also reached his best health conditions for the past 26 years. By the end of 2020, his weight was further reduced to 165 lbs. (BMI 24.4) along with a 6.2% A1C value, without having any medication interventions or insulin injections. The good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his knowledge of chronic diseases, practical lifestyle management experiences, and his developed various high-tech tools contribute to his excellent health status since 1/19/2020.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his glucose measurements every 5 minutes for a total of ~288 times each day. He

has maintained the same measurement pattern to present day. In this study, he uses his CGM sensor glucose at time-interval of 15 minutes (96 data per day). By the way, the difference of averaged sensor glucoses between 5-minutes interval and 15-minutes interval is only 0.3% (114.96 mg/dL for 5-minutes and 115.35 mg/dL for 15-minutes during 2/19/20-7/6/21).

Therefore, over the past 11 years, he could study and analyze the collected 2 million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, and tools from mathematics, physics, engineering, and computer science to conduct his medical research work. His medical research work is based on the aims of achieving both “high precision” with “quantitative proof” in the medical findings.

Weight and FPG

The author has identified a remarkably close relationship and strong connection between his body weight and his FPG in early morning. Both of his weight gain during daytime and weight loss during night sleep are near a constant value which is located within the range of 1.7 lbs to 2.2 lbs. However, his morning body weight, before his breakfast, has a very high correlation of 70% to 90% with his FPG value, depending upon the selected time window of data. Once he establishes the ratio of FPG versus body weight, he would then know his FPG level.

FPG and Initial PPG of Breakfast

From the observation of his collected big data of glucose readings, he can clearly see the initial PPG value of his breakfast (i.e., at 0-minute of a 180-minute duration). It is usually about 8 mg/dL to 11 mg/dL higher than his FPG value in the early morning when the time gap between his wakeup moment and his first-bite of breakfast falls within a time frame of 30 minutes to 45 minutes. This biophysical phenomenon can be explained via a neuro-scientific viewpoint. The FPG at the wakeup moment does not have any influences from either food or exercise. But, when one wakes up from sleeping, the brain detects it immediately that the body needs glucose to support its daily activities. Therefore, the brain issues a marching order to the liver for production or release of glucose and pancreas for secretion of insulin (via beta cells) or glucagon (via alpha cells).

The initial PPG values for his lunch and dinner are higher than the initial PPG value of his breakfast. This is due to his between-meal glucose levels that are usually higher than his FPG in the early morning.

He has found that the gap between his initial daily PPG and FPG (18 mg/dL) is twice larger than the gap between his initial breakfast PPG and FPG (9 mg/dL).

PPG Waveform Construction

Of course, patients can utilize a CGM device to collect their glucose data and then calculate their average value. However, if they can use his intended food intake amount and his planned exercise level to construct or predict a PPG waveform (curve of dataset) beforehand, it would be easier and useful for their T2D control. The following sections list two models, linear elastic glucose theo-

ry model and linear perturbation theory model from his developed GH-Method: math-physical medicine methodology.

Linear Elastic Glucose Theory (LEGT)

Using two perturbation factors, carbohydrates intake grams and post-meal walking steps, his developed LEGT equation is:

$$\begin{aligned} \text{Predicted PPG} \\ = \text{Baseline PPG} + \text{food induced incremental PPG} + \text{exercise induced incremental PPG} \end{aligned}$$

or,

$$\begin{aligned} \text{Predicted PPG} \\ = (\text{FPG} * \text{GH.f}) \\ + (\text{Carbs/sugar} * \text{GH.p}) \\ + (\text{post-meal walking } k\text{-steps} * \text{GH.w}) \end{aligned}$$

Where

$$\begin{aligned} \text{GH.f} = 0.5 \text{ to } 1.5 \text{ (he uses } 1.17) \\ \text{GH.p} = 0.5 \text{ to } 6.0 \text{ (he uses } 0.82) \text{ GH.w} = -2.0 \text{ to } -6.0 \text{ (he uses } -2.66) \end{aligned}$$

The GH.p-Modulus, the most important and difficult multiplier, defines the food induced incremental PPG. It is described as follows:

$$\begin{aligned} \text{Food induced Incremental PPG} \\ = \text{GH.p} * \text{carbs/sugar} \\ \text{or} \\ \text{GH.p} = \text{incremental PPG} / \text{carbs} \end{aligned}$$

In comparison with Young’s modulus equation in strength of engineering materials, such as steel, copper, concrete:

$$E = \text{stress} / \text{strain}$$

where higher E (stiff material) under the same stress would result into less strain.

First-Order Perturbation Theory

The author applies the first-order interpolation perturbation method to obtain his “perturbed PPG” waveforms based on one selected carbs/sugar intake amount functioning as the **perturbation factor**. that is the “Slope”. He uses the “measured PPG” waveform as his reference or baseline waveform for both calculation and comparison.

The following polynomial function is used as the perturbation equation:

$$\begin{aligned} A = f(x) \\ = A_0 + (A_1 * x) + (A_2 * x^{**2}) + (A_3 * x^{**3}) + \dots + (A_n * x^{**n}) \end{aligned}$$

Where A is the perturbed glucose, Ai is the measured glucose, and x is the **perturbation factor** based on a chosen carbs/sugar intake amount.

For this particular study, he chose his A_i as A_1 , where $i=1$. In this way, the above equation can then be simplified into the first-order perturbation equation as follows:

$$A = f(x) = A_0 + (A_1 * x)$$

Or the first-order interpolation perturbation equation can also be expressed in the following general format:

$$A_i = A_1 + (A_2 - A_1) * (\text{slope } 1)$$

Where:

A_1 = original glucose A at time 1

A_2 = advanced glucose A at time 2

$(A_2 - A_1)$ = (Glucose A at Time 2 - Glucose A at Time 1)

The perturbation factor or **Slope** is an arbitrarily selected parameter that controls the size of the perturbation. The author has chosen a function of carbs/sugar intake amount, as his perturbation factor or slope, which is further defined below:

In this particular study, he selects 10 grams as the low-bound carbs/sugar amount and 20 grams as the high-bound carbs/sugar amount, while using 14 grams as his selected or perturbed carbs/sugar amount.

Slope

$$= (\text{Selected Carbs} - \text{Low-bound Carbs}) / (\text{High-bound Carbs} - \text{Low-bound Carbs})$$

Therefore, in this study, his slope or perturbation factor value has been calculated as:

$$\begin{aligned} \text{Slope from Carbs} &= (14 - 10) / (20 - 10) \\ &= 0.4 \text{ or } 40\% \end{aligned}$$

Daily Sensor Glucose (eAG) and Sensor HbA1C

He has chosen a simple formula for his approximated sensor-based daily glucose (eAG) which disregards all of the between-meals and pre-bed glucose values. Actually, PPG plays a predominant role of HbA1C and FPG plays a predominant role of health state of Pancreatic beta cells which also directly influence the HbA1C level.

The eAG formula is expressed as follows:

$$\text{Daily sensor glucose (eAG)} = (FPG + (PPG * 3)) / 4$$

Furthermore, he has chosen a simple conversion factor (CF) of 18.86 to calculate his corresponding sensor-based A1C value as follows:

$$\text{Sensor A1C} = (\text{sensor daily glucose eAG}) / CF = eAG / 18.86$$

Results

Figure 1 shows the relationship among weight, FPG and initial breakfast PPG with the following key data:

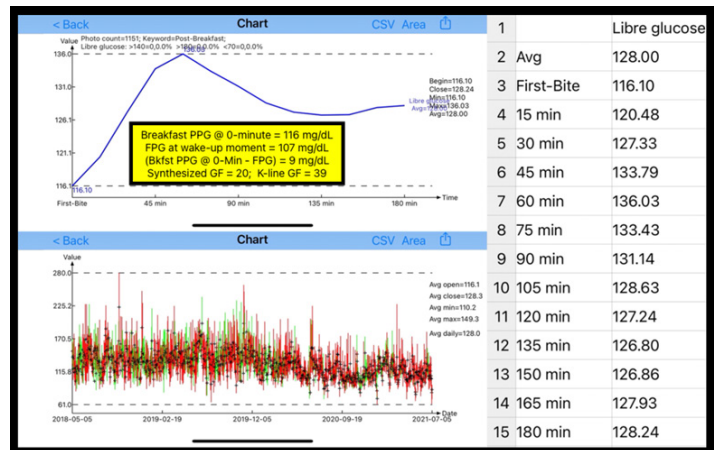


Figure 1: weight, FPG, Initial PPG

Weight = 170.13 lbs.
 FPG = 106.72 mg/dL
 R of FPG vs. Weight = 71.7%
 FPG / Weight = 62.5%
 Initial breakfast PPG = 116.1 mg/dL
 Glucose difference
 = Initial breakfast PPG - FPG
 = 9.4 mg /dL
 GH.f = initial PPG / FPG = 1.17

Therefore,

FPG

$$= \text{Weight} * (\text{FPG}/\text{Weight})$$

Initial PPG

$$= \text{FPG} + \text{Glucose difference}$$

Figure 2 depicts the synthesized breakfast PPG and its associated candlestick K-line chart.

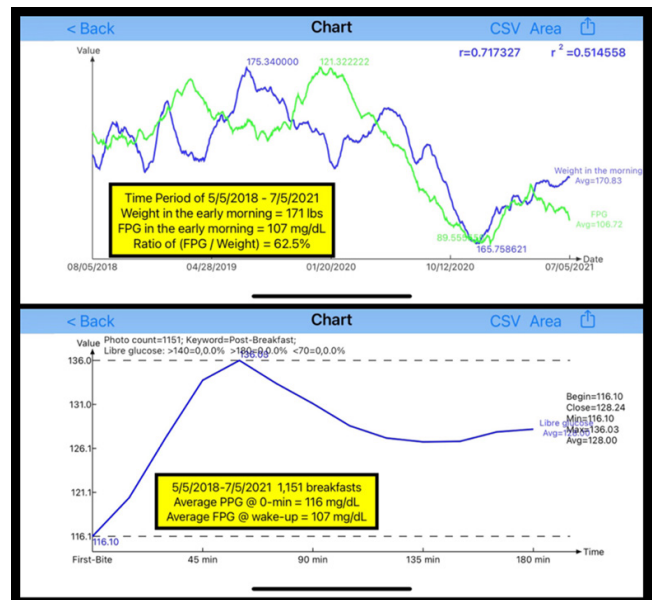


Figure 2: Synthesized 1,151 breakfast PPG and breakfast PPG

k-line chart

Figure 3 reveals the synthesized total of 3,525 meals' PPG and associated candlestick K-line chart.

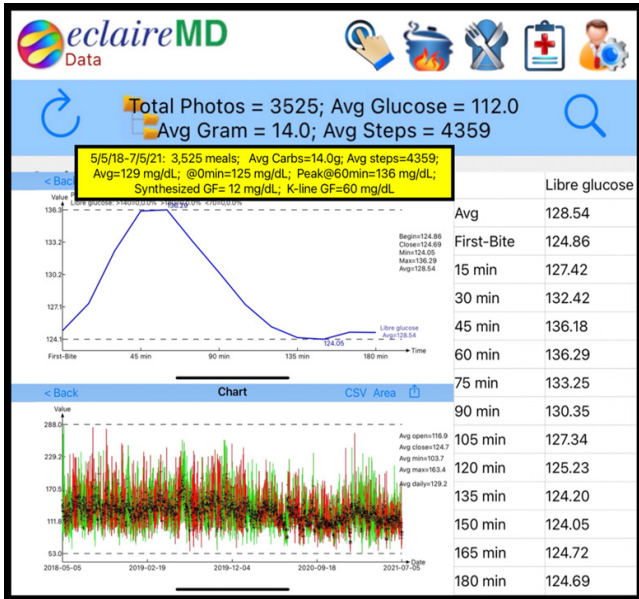


Figure 3: Synthesized total 3,525 PPG and total PPG k-line chart

Figure 4 reflects the OHCA (i.e., LEGT) model with its associated calculation table.

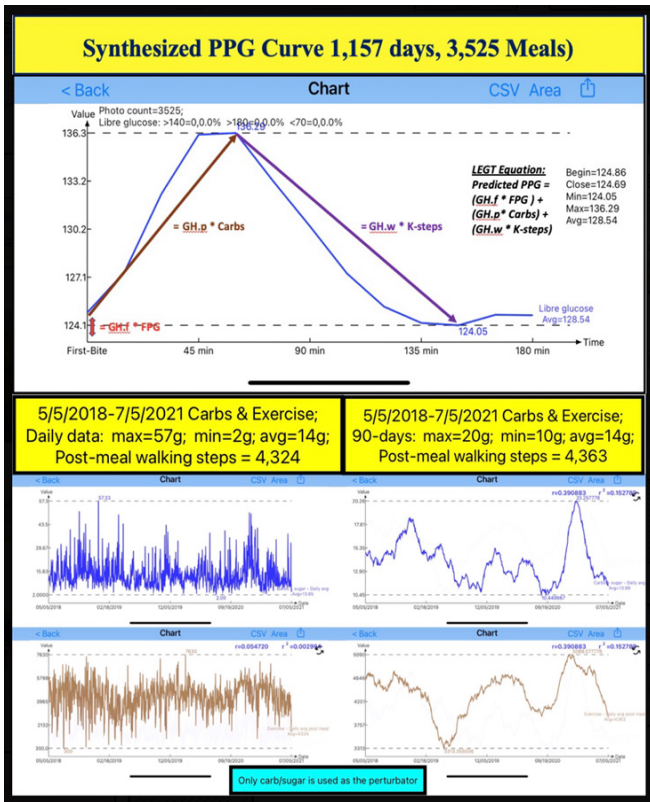


Figure 4: OHCA chart (LEGT) of PPG waveform, plus carbs/sug-

ar amount & post-meal waking steps

Figure 5 illustrates LEGT PPG vs. measured PPG waveforms and their associated calculation table. Their prediction accuracy is 99% and correlation is 83%.

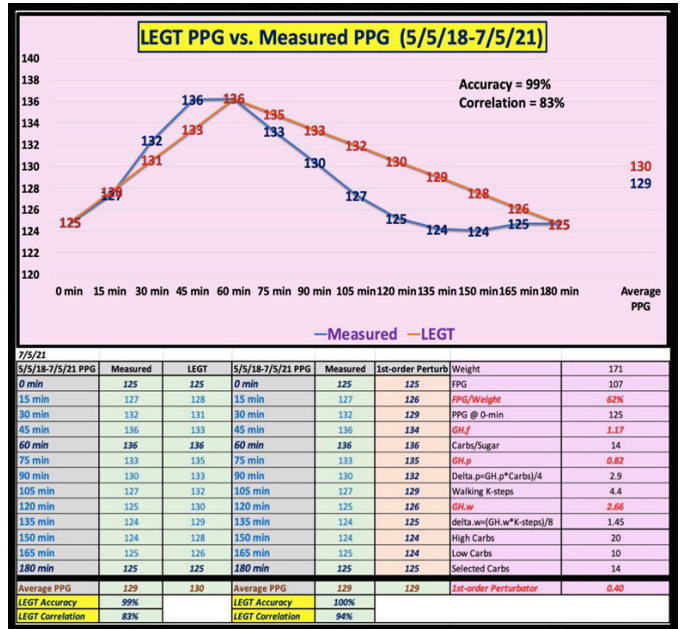


Figure 5: LEGT PPG versus measured PPG

Figure 6 indicates the perturbed PPG vs. measured PPG waveforms and their associated calculation table. Their prediction accuracy is 100% and correlation is 94%.

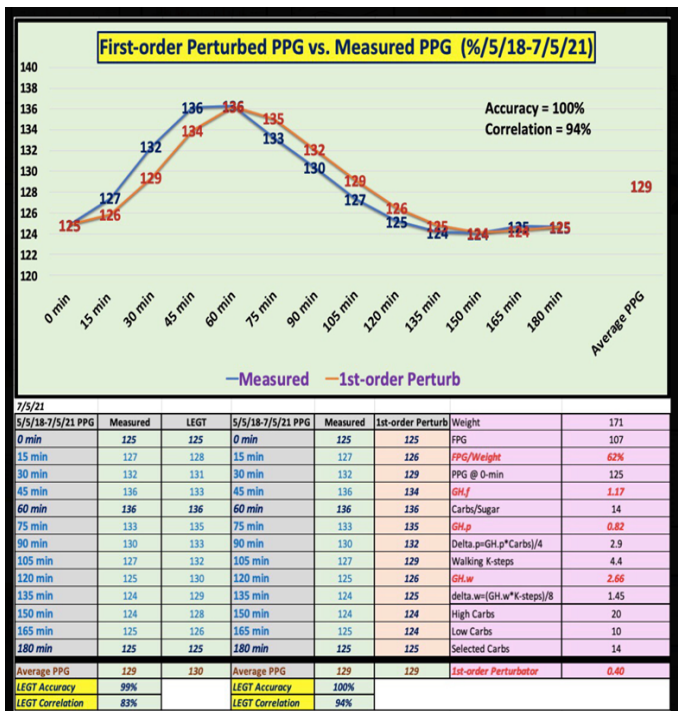


Figure 6: Perturbed PPG versus measured PPG

Figure 7 re-combines the results from LEGT PPG vs. measured PPG (Figure 5) and Perturbed PPG vs. measured PPG (Figure 6) and their associated glucose values and A1C as follows:

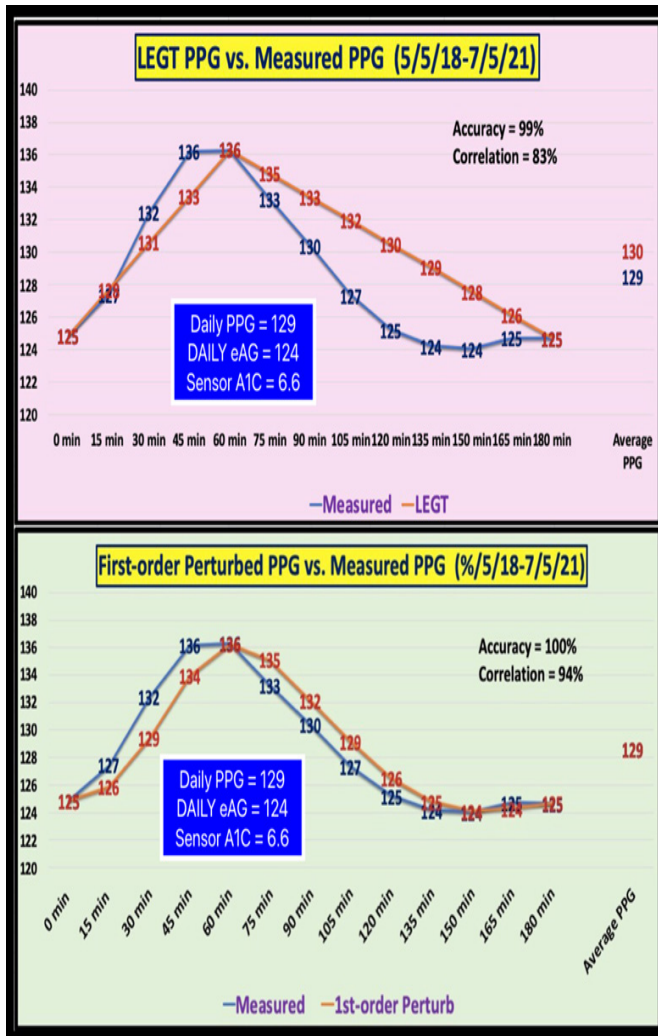


Figure 7: Glucose and A1C values of LGT VS. Measured and Perturbed vs. Measured

Daily PPG = 129 mg/dL
Daily eAG = 124 mg/dL
A1C = 6.6%

Figure 8 demonstrates the “time-series” diagram results of 90-days moving average sensor FPG, PPG, eAG, and HbA1C values as follows:

FPG = 109 mg/dL
PPG = 129 mg/dL
eAG = 124 mg/dL
A1C = 6.6%

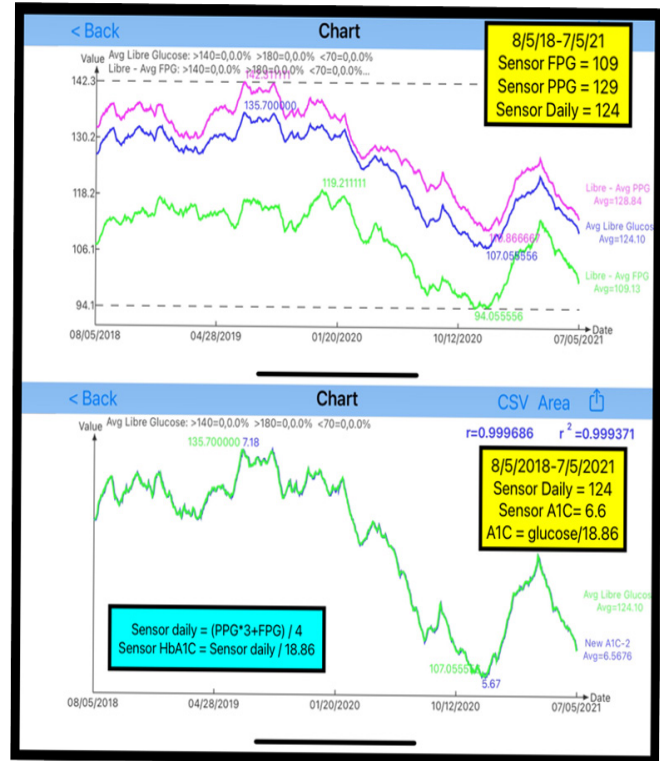


Figure 8: A1C value

Conclusions

In summary, this described linear approximation model of type 2 diabetes (T2D) control is contingent on various findings in each stage of his research work. By using observation, analysis, induction, verification, and simplification, he gradually discovers the evolutionary steps of application of his GH-method: math-physical medicine (MPM) methodology on diabetes.

In this particular article, he utilized his own CGM sensor-based glucose data from 5/5/2018 to 7/5/2021 to illustrate and verify his developed simple linear approximation model.

There are five key steps in this simple linear model:

1. weight to FPG in 2015 & 2016,
2. FPG to initial PPG in 2017,
3. eAG from both FPG and PPG in 2018,
4. construction of PPG waveforms in 2019 & 2020,
5. sensor-based A1C calculation in 2021.

Among these 5 steps, the fourth step of the construction of PPG waveform is the most sophisticated one.

The following listed data with their embedded formulas or mathematical methods recaps his finding results:

Weight = 171 lbs (*63%)

FPG = 107 mg/dL (+9 mg/dL or +18 mg/dL)

to get the initial of breakfast PPG

= 116 mg/dL

or the Initial of daily PPG

= 125 mg/dL

via LEGT model, to get average PPG = 130 mg/dL (99% Accuracy)

via Perturbation, to get average PPG = 129 mg/dL (100% Accuracy)

This simple linear approximation model has achieved an extremely high 99%-100% prediction accuracy with a remarkably high 83%-94% correlation coefficient (R) that is the waveform shape similarity between measured PPG and approximated PPG [1-2].

References

1. Hsu Gerald C (2020) 53 MPM methodology paper numbers: 9, 13, 14, 19, 20, 21, 22, 35, 45, 53, 54a, 54b, 66, 76, 78, 79, 82, 84, 89, 90, 91a, 91, 97, 105, 106, 125, 140, 245, 246, 249, 266, 267, 270, 271, 271a, 272, 272a, 276, 286, 290, 294, 310, 312, 320, 386, 387, 397, 421, 447, 453, 457, 458. www.eclaircmd.com
2. Hsu Gerald C (2021) 53 LEGT and perturbation theory applications paper numbers: 152, 154, 345, 346, 349, 350, 351a, 351b, 352, 356, 357, 358, 359, 360, 361, 362, 363, 364, 365, 367, 369, 370, 371, 396,401, 402, 403, 411, 412, 413, 414, 415, 416, 417, 418, 420, 422, 423, 424, 425, 426,427, 428, 429, 430, 440, 460, 462, 463, 464, 470, 471, 472. www.eclaircmd.com

Copyright: ©2021 Gerald C Hsu. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.