

## Another Geometry Equation using Linear Elastic Glucose Theory to Estimate Average Sensor PPG and Finger PPG based on GH-Method: Math-Physical Medicine, LEGT Part 29 (No. 418)

Gerald C Hsu

EclaireMD Foundation, USA

\*Corresponding author

Gerald C Hsu, EclaireMD Foundation, USA

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### Abstract

On 10/14/2020, the author wrote his first research note on his developed linear elastic glucose theory (LEGT). Over the past 5+ months, he has continuously conducted his research on this subject, where he completed his research note on a summary report, No. 415, LEGT Part 26 on 3/15/2021.

In the LEGT research note, No. 416, Part 27, he applied simple geometry to derive a set of equations in estimating the average LEGT sensor PPG and LEGT finger PPG values known as Equation A, which were based on values of P1, P2, and P3. In the current research note, No. 418, Part 28, he derived another set of equations for the same two PPG values known as Equation B, which were based on values of Weight or FPG, carbs/sugar intake amount, and post-meal walking k-steps.

In summary, similar to the Young's modulus of engineering materials, the GH.p-Modulus for diet is the most important GH-Modulus of biomedicine applications. This is related to and dependent on the patient's overall metabolic conditions, age, lifestyle, health, medical diseases, types of food, amount of carbs/sugar intake, and to some degree the chosen time-window for certain analyses. Nevertheless, its linear and elastic behaviors and general glucose characteristics are quite comparable to the Young's modulus of stress and strain in theory of elasticity of engineering. All of the author's collected glucose data to date present their behaviors within the defined "elastic" region. Therefore, his developed LEGT would be useful for other type 2 diabetes (T2D) patients to control their diabetes conditions.

### Introduction

On 10/14/2020, the author wrote his first research note on his developed linear elastic glucose theory (LEGT). Over the past 5+ months, he has continuously conducted his research on this subject, where he completed his research note on a summary report, No. 415, LEGT Part 26 on 3/15/2021.

In the LEGT research note, No. 416, Part 27, he applied simple geometry to derive a set of equations in estimating the average LEGT sensor PPG and LEGT finger PPG values known as Equation A, which were based on values of P1, P2, and P3. In the current research note, No. 418, Part 28, he derived another set of equations for the same two PPG values known as Equation B, which were based on values of Weight or FPG, carbs/sugar intake amount, and post-meal walking k-steps.

### Methods

#### 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 (Reference 1) describes his MPM methodology in a general conceptual format. The second paper, No. 387 (Reference 2) 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 (Reference 3) depicts a general flow diagram containing ~10 key MPM research methods and different tools.

## Highlights of his Developed Linear Elastic Glucose Theory (LEGT)

The author self-studied internal medicine, including endocrinology and food nutrition over a 4-year period from 2010 to 2013. By the end of 2013, he has learned the primary connecting pathway moving from lifestyle to metabolism and immunity, which are two sides of the same coin, and then moving to both chronic diseases (caused by metabolic disorders) and infectious diseases (defended by our immune system), and finally to induce all kinds of diseases which lead to death.

Therefore, in 2014, he spent the entire year to develop a mathematical model of metabolism using topology concept of mathematics and finite element method of engineering which includes 10 categories and near 500 elements. All of its input data are more than 2 million thus far.

Due to the fact that PPG is the major factor of daily glucose composition and HbA1C measurement which affects diabetes conditions and its complications directly. Therefore, starting from 2015, he started to develop his prediction model for post-prandial plasma glucose (PPG). He has identified approximately 19 influential factors of PPG formation, where the health state of pancreatic beta cells insulin secretion (quantity) and insulin resistance (quality) are the most important and the fundamental factor. Since it occupies more than 2/3 of total influences on PPG, he choose it as the "baseline PPG". Once removing this biomedical factor of insulin (~50% to 80% or 67% of contribution), the other 18 remaining lifestyle details, ranging from ~20% to 50% or 33%, contribute to the final PPG formation. Taking a macro-view of PPG formation, the pancreatic beta cells accounts for ~50% to 67% and diet of lifestyle provides ~50%, while diet contributes ~33% and post-meal walking exercise contributes about -17% (negative correlation). Although the combined diet and exercise are about 1/3 of PPG, they are the only factors that diabetes patients can control. The current diabetes treatments by physicians to stabilize glucose levels are through medications and/or insulin injections. Unfortunately, this type of treatment attempts to alter the external symptom (i.e., output only) of the endocrinological diabetes disease but does not cure or even improve parts of the root cause. Only a long-term persistent effort of lifestyle management can truly "repair or improve" the damaged pancreatic beta cells.

Using various GH-Method: math-physical medicine tools on his collected big data, *he had an intuition that the existence for a linear relationship between his measure PPG and carbs/sugar intake amount with a multiplying coefficient around 1.0 to 3.0 for a longer time-window or 1.8 to 2.5 for a specific shorter time-window.*

In order to solve the puzzle of the predicted PPG, the first task is to identify an accurate but easy way to estimate carbs/sugar intake amount. Utilizing optical physics (relationship among visible food color, internal wavelength, molecular structure, and nutritional ingredients), big data analytics (~6 million collected food nutritional data and 160 million digits of each meal photo), and AI (machine learning and auto-correction), he developed a computer software program to predict the carbs/sugar amount in his food or meals via

a picture with a prediction accuracy of >99% (for over 3,000 meals or food pictures). He then applied this GH.p-Modulus of linear coefficient at 1.8 to 2.5 to multiply his estimated carbs/sugar amount from the AI tool in order to obtain the incremental PPG from food. This observed linear coefficient of 1.8 to 2.5 was his first identified GH-modulus, the GH.p-Modulus.

Diet is the most complicated part of this puzzle. Actually, a predicted PPG wave is a nonlinear mathematical problem with a dynamic physical phenomenon. In order to simplify this difficult task at hand, he has broken down this synthesized nonlinear system into 3 simpler linear systems or 3 straight-line segments, which are the pancreatic beta cells' insulin, diet for rising glucose, and exercise for declining glucose.

After 9-months of struggling during 2015-2016, in the early morning of 3/16/2016, he finally discovered a strong correlation (>80% of R, the correlation coefficient) existing between his body weight and his collected fasting plasma glucose (FPG) by having an "out-of-box" thinking. Since both weight and FPG belong to the output category of the biomedical system, while lifestyle details belong to the input category. As a trained engineer, he was taught to always seek and identify those relationships existing between inputs and outputs, not just among outputs or among inputs. This phenomenon has proven that, in the biomedical system, its inputs and its outputs are inter-wined with each other.

From 2017 to 2020, he utilized 7 to 8 different research angles to investigate his pancreatic beta cells' "self-repair" situation. Since there is no food or exercise associated with glucose during sleep hours to confuse the equation, by using the FPG data, a long-term record of FPG or weight can serve as a reliable "benchmark indicator" for the pancreatic health state. As a result, he identified his second GH-Modulus, the GH.f-Modulus, to transform either weight or FPG into baseline PPG.

Relatively speaking, exercise is a much easier subject to be dealt with. From his trial-and-error effort for finding the linear coefficient between the post-meal walking k-steps (1,000-steps) and reduction amount of PPG, he identified that PPG would be reduced by 5 to 6 mg/dL for every thousand steps after having meals (about 10 minutes of walking). Therefore, he has chosen -5 to -6 as his third GH-Modulus, the GH.w-Modulus.

By combining these three linear models together, he obtained a "pseudo-linear" model (i.e., with 3 straight lines) to be served as his predicted PPG as shown in Figure 1. In Figure 1, this pseudo-linear model is superposed with a synthesized nonlinear PPG wave model over 180 minutes time-span from his collected 3,255 meals data over a period of 1,085 days from 5/5/2018 to 3/15/2021.

If readers are interested in learning his step-by-step development and more detailed explanation of the predicted PPG equation using LEGT, they can read the author's published papers listed in References 4 through 29. Now, he displays his LEGT equation below (see Figure 1).

Sensor PPG	LEGT Pre-virus	LEGT Virus	LEGT Total
0 min	129	118	124
15 min	141	126	130
30 min	153	134	136
45 min	150	142	141
60 min	148	137	147
75 min	146	132	143
90 min	144	127	139
105 min	141	122	135
120 min	139	117	130
135 min	137	112	126
150 min	134	107	122
165 min	132	102	118
180 min	130	97	114
Average LEGT PPG	140	121	131
	Pre-virus	Virus	Total
P1	129	118	124
P2	148	137	147
P3	130	97	114
Total	1793	1550	1705
Avg. LEGT Sensor (Equation A)	138	119	131
120-min Finger (Equation A)	121	101	114
GH.p	1.70	1.70	1.64
GH.w	-5.50	-9.90	-7.70
Carbs/Sugar grams	14.2	13.8	14.1
Walking K-steps	4.2	4.5	4.3
Avg. LEGT Sensor (Equation B)	141	119	130
120-min Finger (Equation B)	123	104	114

**Figure 1:** Three linear segments of a synthesized PPG wave using three GH-Moduli

The LEGT equation is:

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

or,

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

Based on his experiences on utilizing his GH-Modulus, the GH.f should fall into the range between 0.6 to 1.0. Frequently, for his own case, he choose 0.6 if using Weight or 0.97 to 1.0 if using FPG to start this linear equation calculation. He also choose the GH.w as -5.0 for most of his exercise cases. Finally, the GH.p-Modulus, the most important and difficult multiplier, defines the food induced incremental PPG. It is described again as follows:

$$\text{Food induced Incremental PPG} = \text{GH.p} * \text{carbs/sugar}$$

or

$$\text{GH.p} = \text{incremental PPG} / \text{carbs}$$

In comparison with Young's modulus equation:

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

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

If we consider carbs/sugar intake similar to stress and incremental PPG similar to strain, then the biomedical GH.p-modulus and engineering E of Young's Modulus would have a "reciprocal" relationship to each other.

Therefore, a higher E of Young's modulus value is equivalent to a lower GH.p-Modulus value. If a higher E (stiff material) under the same stress level would result in a lower strain. This

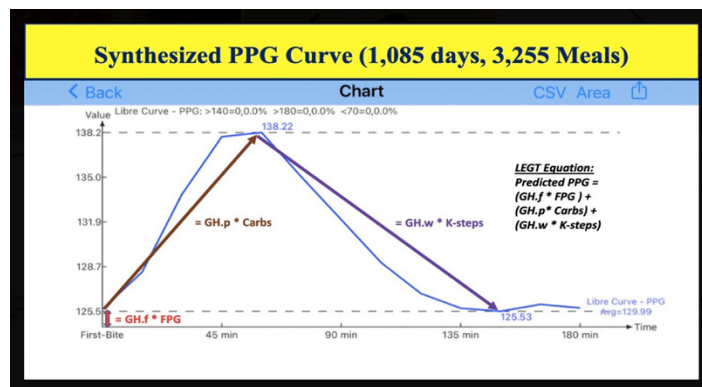
is similar to a lower GH.p-Modulus under the same carbs/sugar intake amount which would result in a smaller amount of incremental PPG; or the same GH.p-Modulus with the smaller carbs/sugar intake amount which would result in a smaller amount of incremental PPG.

The above explanation provides an analogy of LEGT in biomedicine with the theory of elasticity in engineering.

### Detailed Description of the process using LEGT PPG Model

This section will illustrate the step-by-step development of his developed LEGT PPG model.

The first step discusses the baseline PPG which is the PPG level at the time instant of 0-minute i.e., the first bite of meal. As mentioned above, the early morning glucose level after waking up is a good benchmark indicator for the pancreatic health state. The FPG value has a different mechanism from the insulin generating capability, but it is directly proportional to the health state of the pancreatic beta cells insulin. Furthermore, FPG and weight have an extremely high correlation coefficient (>80%) between them (see Figure 2). Most diabetes patients know their daily weight, where some of them monitor their FPG on a regular basis. Therefore, depending on the data availability for either weight or FPG, patients may choose one of the following two equations to use:



**Figure 2:** Data table using both Equation A and Equation B for pre-virus and virus periods

$$\text{Baseline PPG} = (0.6 - 0.7) * \text{weight}$$

$$\text{Baseline PPG} = (0.9 - 1.0) * \text{FPG}$$

The second step deliberates the rising PPG values from the starting time at 0-minute (defined as P1 value) to its peak at 45-minutes to 75-minutes. Let us assume the PPG value reaches to its peak at 60-minutes (defined as P2 value). During this time frame, the major fuel for this action of PPG rising is resulted from carbs/sugar intake with meal; therefore, the second segment of LEGT PPG equation can be listed below:

$$\text{Incremental PPG amount} = \text{P2} - \text{P1} = (\text{carbs/sugar intake grams}) * \text{GH.p}$$

Where  $GH.p$ -Modulus range is between 1.0 and 6.0. But the narrower range of 1.8-2.5 is more suitable for many patients under normal diet situations.

During this second step, patients can utilize the author's developed AI food nutrition program or rely on their own learned knowledge about carbs/sugar amount for each meal in completing the calculation for the second stage of diet.

The third step examines the PPG value reduction between time instant of 60-minutes to 180-minutes (defined as P3 value). It should add another time instant of 120-minutes (defined as Finger PPG value), where the PPG value corresponds to the advice of physicians to diabetes patients on measuring their PPG at two hours after the first bite of meals using the finger-piercing method. The PPG reduction amount can be calculated using the following equation:

$$PPG \text{ reduction amount} = P2 - P3 = (\text{post-meal walking } k\text{-steps}) * GH.w$$

Where  $GH.w$ -Modulus range is between -5 and -6, but the selected  $GH.w$  value of -5 is more suitable for patients under normal walking conditions. Other types of exercise are also acceptable but its related  $GH.w$  value must be re-evaluated carefully via more experiments.

At this stage, a natural biomedical nonlinear PPG wave can then be replaced by three straight-lines and converts the nonlinear real PPG wave into a linear representation with a high accuracy of prediction, but it is a simpler way to distinguish PPG situations.

For the LEGT PPG case, its average glucose values are listed based on a set of geometry equations, or Equation A, which use the values of P1, P2, and P3.

$$\text{Average sensor LEGT PPG} = (2.5 * P1 + 6.0 * P2 + 4.5 * P3) / 13$$

and

$$\text{Finger LEGT PPG} = 0.87 * (\text{sensor LEGT PPG at 120-minutes}) = 0.87 * (P2 + P3) / 2$$

In this article, the author extended Equation A into Equation B, which uses weight or FPG, carbs/sugar intake amount, and post-meal walking k-steps, without touching P1, P2, P3.

By starting with the following three initial definitions:

$$P1 = GH.f * \text{weight or FPG}$$

$$P2 = P1 + GH.p * \text{carbs}$$

$$P3 = P2 + GH.w * \text{k-steps}$$

We can then further derive them into the following Equation B:

$$\text{Average LEGT sensor PPG} = P1 + 0.8077 * (GH.p * \text{Carbs}) + 0.3462 * (GH.w * \text{K-steps})$$

and

$$\text{LEGT finger PPG (at 120-min)} = 0.087 * (P1 + GH.P * \text{Carbs}) + 0.435 * (GH.w * \text{K-steps}) =$$

We can combine both Equation A and Equation B together as follows:

$$\text{Average LEGT sensor PPG} = (2.5 * P1 + 6.0 * P2 + 4.5 * P3) / 13 = P1 + 0.8077 * (GH.p * \text{Carbs}) + 0.3462 * (GH.w * \text{K-steps})$$

$$\text{LEGT finger PPG (at 120-min)} = 1/2 * (P2 + P3) = 0.087 * (P1 + GH.P * \text{Carbs}) + 0.435 * (GH.w * \text{K-steps})$$

The above descriptions, including the two important LEGT equations and three GH-Modulus, are the building blocks of the LEGT PPG program.

For most T2D patients, they just enter their weight or FPG values, average carb/sugar intake grams, and post-meal walking k-steps, over a selected time period, into the program. Then, the AI assistant will perform all of the calculations.

## Results

Figure 1 shows LEGT equations graphically. It illustrates three straight line segments of the LEGT PPG model with three associated GH-Moduli.

Figure 2 reflects the data table of input data and its calculated results using both Equation A and Equation B.

Figure 3 depicts an extremely high equivalence between using Equations A and B to obtain the average LEGT sensor PPG and LEGT finger PPG at 120-minutes. The minor discrepancies are results from truncation, rounding off numbers, or some small error in inputs.

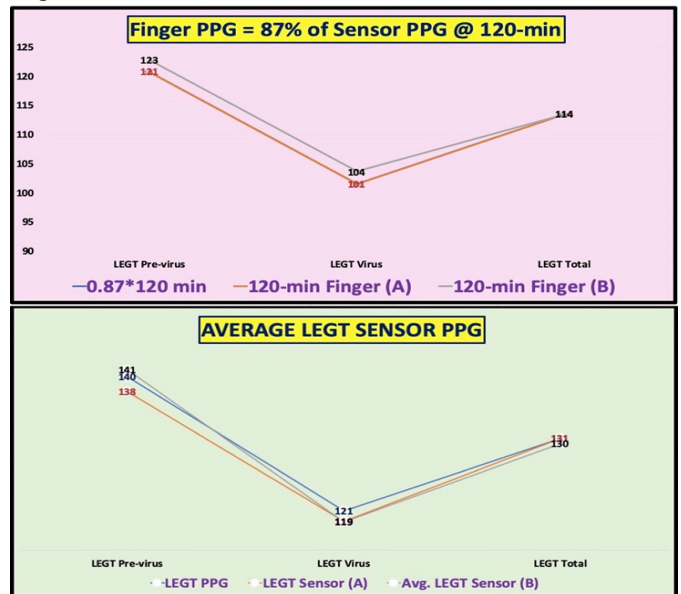


Figure 3: Finger LEGT PPG and Sensor LEGT PPG for three

periods (pre- virus, virus, total)

Figures 4 reveals the three GH-moduli used in calculation. *Got pre-virus and virus periods, those three GH-moduli values are:*

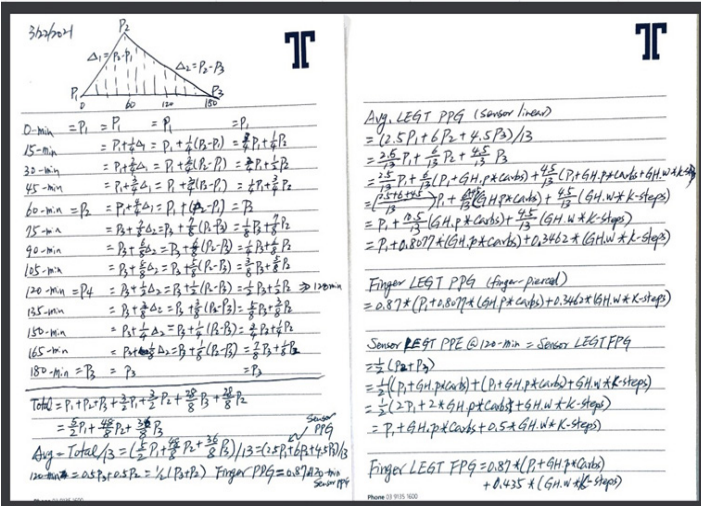
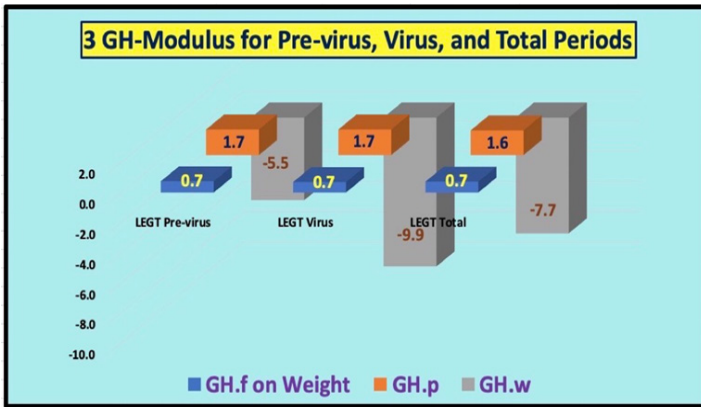


Figure 4: Three GH-moduli and hand-written equation derivation

$GH.f = 0.7$   
 $GH.p = 1.6 \text{ to } 1.7$   
 $GH.w = -5.5 \text{ to } -0.9$  (average -7.7)

Figure 4 also displays the author’s original handwritten note of the LEGT equation derivation.

*It is interesting to list another set of GH-moduli from his long 12-year period. These two sets of GH-moduli are quite close to each other, where the appropriate GH-Modulus for the 12-year period are listed below:*

$GH.f = 0.73$   
 $GH.p = 1.93$   
 $GH.w = -6.2$

Figure 5 is a conceptual diagram of LEGT.

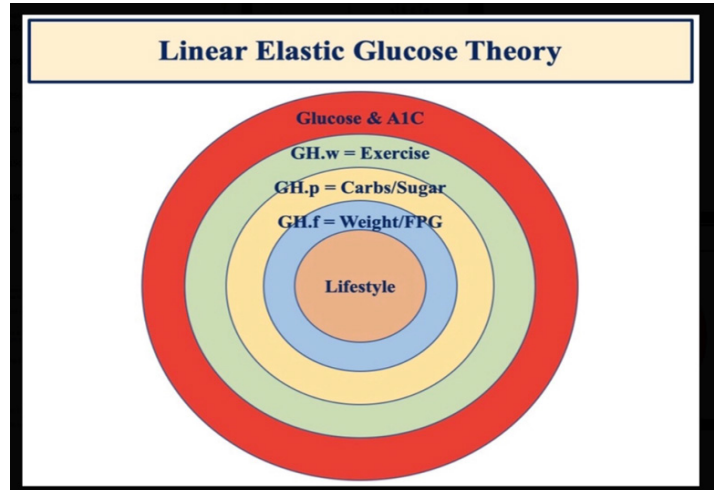


Figure 5: Conceptual diagram of LEGT

### Conclusions

In summary, similar to the Young’s modulus of engineering materials, the GH.p-Modulus for diet is the most important GH-Modulus of biomedicine applications. This is related to and dependent on the patient’s overall metabolic conditions, age, lifestyle, health, medical diseases, types of food, amount of carbs/sugar intake, and to some degree, the chosen time-window for certain analyses. Nevertheless, its linear and elastic behaviors and general glucose characteristics are quite comparable to the Young’s modulus of stress and strain in theory of elasticity of engineering. All of the author’s collected glucose data to date present their behaviors within the defined “elastic” region. Therefore, his developed LEGT would be useful for other type 2 diabetes (T2D) patients to control their diabetes conditions [1-31].

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