

Coefficient of GH.f-Modulus in the Linear Elastic Fasting Plasma Glucose Behavior Study Based on Health Data of Three Diabetes Patients Using the GH-Method: Math-Physical Medicine, Part 4 (No. 356)

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Abstract

This article is Part 4 of the author's linear elastic glucose behavior study, which focuses on fasting plasma glucose (FPG) component. It is the continuation of his previous three studies, Parts 1, 2, and 3, on linear elastic postprandial plasma glucose (PPG) behaviors.

Here is his defined linear elastic FPG equation:

$$FPG = GH.f\text{-modulus} * Weight$$

Where Weight is the input component (similar to stress) and FPG is the output component (similar to strain). The close relationship between Weight and FPG can also be found in his previous published medical papers (Reference 10).

GH.f-modulus is a newly defined coefficient to connect both weight and FPG, similar to the theory of elasticity in engineering:

$$Stress = Young's\ modulus * Strain$$

Where Young's modulus connects both stress and strain except **Young's modulus and GH.f-modulus are reciprocal to each other.**

The author is able to connect this biomedical FPG equation with the basic concept of linear elasticity, which involves stress, along with the Young's modulus of strength of materials in structural & mechanical engineering. He uses the collected data of daily body weight and daily FPG data from three type 2 diabetes (T2D) patients with separate severity levels of obesity and diabetes within three different time ranges. In addition, he uses an identical 8-month period of collected data for the three patients to conduct his analysis. He demonstrated once again that using GH.f-modulus, a "pseudo-linear" relationship connecting both weight and FPG exists in all three clinical cases, except the value of this coefficient depends on the individual patient's severity level of chronic diseases, specifically obesity and diabetes.

The main objectives of this study is threefold. First, it is to of-

fer a simpler FPG prediction equation to the patients. Second, it is to prove that similar to GH.p-modulus for PPG, the coefficient of GH.f-modulus indeed varies with the severity of chronic diseases in these clinical cases. Third, this constant coefficient of GH.f-modulus also differs from one-time range to another due to dynamic behavior, because blood is a living organic material.

The 7-month average value of each monthly M2 variables (i.e., GH-modulus) are 3.7, 2.6, and 1.0, and with an average measured PPG values at 122 mg/dL, 114 md/dL, and 109 mg/dL, for Case A, Case B, and Case C, respectively, which are ranked according to the severity of their diabetes conditions.

In summary, the higher the M2, the higher values of both x (carbs/sugar intake amount) and y (incremental PPG amount) become,

and the higher predicted and measured PPG values are. The key conclusion from these three clinical observations is that the M2 values are varying based on the patients' body conditions (liver and pancreas), especially their diabetes severity. This is similar to the different inorganic materials having the different Young's modulus values, such as nylon ~3 versus steel ~200.

The article represents the author's special interest in using math-physical and engineering modeling methodologies to investigate various biomedical problems. The methodology and approach are a result of his specific academic background and various professional experiences prior to the start of his medical research work in 2010. Therefore, he has been trying to link his newly acquired biomedical knowledge over the past decade with his previously acquired knowledge of mathematics, physics, computer science, and engineering for over 40 years.

The human body is the most complex system he has dealt with, which includes aerospace, navy defense, nuclear power, computers, and semiconductors. By applying his previous acquired knowledge to his newly found interest of medicine, he can discover many hidden facts or truths inside the biomedical systems. Many basic concepts, theoretical frame of thoughts, and practical modeling techniques from his fundamental disciplines in the past can be applied to his medical research endeavor. After all, science is based on theory from creation and proof via evidence, and as long as we can discover hidden truths, it does not matter which method we use and which option we take. This is the foundation of the GH-Method: math-physics medicine.

The author has spent four decades as a practical engineer and understands the importance of basic concepts, sophisticated theories, and practical equations, which serve as the necessary background of all kinds of applications. Therefore, he spent his time and energy to investigate glucose related subjects using variety of methods he studied in the past, including this particular interesting stress-strain approach. On the other hand, he also realizes the importance and urgency on helping diabetes patients to control their glucoses. That is why, over the past few years, he has continuously simplified his findings about diabetes and try to derive more useful formulas and simple tools for meeting the general public's interest on controlling chronic diseases and their complications to reduce their pain and probability of death.

Introduction

This article is Part 4 of the author's linear elastic glucose behavior study, which focuses on fasting plasma glucose (FPG) component. It is the continuation of his previous three studies, Parts 1, 2, and 3, on linear elastic postprandial plasma glucose (PPG) behaviors.

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The main objectives of this study is threefold. First, it is to offer a simpler FPG prediction equation to the patients. Second, it is to prove that similar to GH.p-modulus for PPG, the coefficient of GH.f-modulus indeed varies with the severity of chronic diseases in these clinical cases. Third, this constant coefficient of GH.f-modulus also differs from one-time range to another due to dynamic behavior, because blood is a living organic material.

Patients with varying chronic diseases would have different coefficient of GH.f-modulus. Both Case A and Case B are long-term T2D patients; however, their weights are still within the boundary of normal and slightly overweight with BMI around 25. Therefore, using 14 semi-annual periods for Case A and 10 months for Case B, their coefficients are the same at 0.67. However, due to Case A's stringent lifestyle management to control his diabetes, his weight and glucoses, including FPG, have reduced significantly, especially in 2020 where his coefficient became 0.59 in comparison with Case B's 0.66.

Case C is another story. His extreme-obese condition (BMI at 40.7) is much more serious than his diabetes conditions with a 4-year history. In order to compensate for his heavy weight, he must have a lower value of the GH.f-modulus (his coefficient of 0.36 is at 54% level of 0.67 for both Case A and Case B) in order to match with his measured FPG level (almost normal).

At first glance of this coefficient, it appears that it as a variable, rather than a constant. However, by examining their values within a reasonable time span, they do not vary that much. That is why it is called a "pseudo-linear" relationship. Once we have collected sufficient data for a particular time period, we can then easily figure out the suitable coefficients for both FPG and PPG, i.e. GH.f-modulus and GH.p-modulus respectively, to be used in glucose predictions.

Methods Background

To learn more about the author's GH-Method: math-physical medicine (MPM) methodology, readers can refer to his article to under-

stand his developed MPM analysis method in Reference 1.

Highlights of his Related Research

In 2015 and 2016, the author decomposed the PPG waveforms (data curves) into 19 influential components and identified carbs/ sugar intake amount and post-meal walking exercise contributing to approximately 40% of PPG formation, respectively. Therefore, he could safely discount the importance of the remaining ~20% contribution by the 16 other influential components.

In March of 2017, he also detected that body weight contributes to over 85% to fasting plasma glucose (FPG) formation. Furthermore, he identified the correlation coefficient between weight and FPG are higher than 90% for different diabetes patients. In addition, he has found other 4 secondary contribution factors of FPG formation.

In 2019, all of his developed prediction mathematical models for both FPG and PPG have achieved high percentages of prediction accuracy, but he also realized that his prediction models are too difficult for use by the general public. Their theoretical background and sophisticated methods would be difficult for healthcare professionals and diabetes patients to understand, let alone use them in their daily life for diabetes control. Therefore, he supplemented his complex models with a simple linear equation of predicted FPG and predicted PPG (see References 2, 3, and 4).

Stress, Strain, & Young's Modulus

Prior to his medical research work, he was an engineer in the various fields of structural engineering (aerospace, naval defense, and earthquake engineering), mechanical engineering (nuclear power plant equipment's, and computer-aided-design), and electronics engineering (computers, semiconductors, graphic software, and software robot).

The following excerpts come from internet public domain, including Google and Wikipedia:

“Strain - ϵ

Strain is the "deformation of a solid due to stress" - change in dimension divided by the original value of the dimension - and can be expressed as

$$\epsilon = dL / L$$

where

ϵ = strain (m/m, in/in)

dL = elongation or compression (offset) of object (m, in)

L = length of object (m, in)

Stress - σ

Stress is force per unit area and can be expressed as

$$\sigma = F / A$$

where

σ = stress (N/m², lb/in², psi)

F = applied force (N, lb)

A = stress area of object (m², in²)

Stress includes tensile stress, compressible stress, shearing stress, etc.

E , Young's modulus

It can be expressed as:

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

$$= \sigma / \epsilon$$

$$= (F / A) / (dL / L)$$

where

E = Young's Modulus of Elasticity (Pa, N/m², lb/in², psi) was named after the 18th-century English physicist Thomas Young.

Elasticity

Elasticity is a property of an object or material indicating how it will restore it to its original shape after distortion. A spring is an example of an elastic object - when stretched; it exerts a restoring force, which tends to bring it back to its original length (Figure 1).

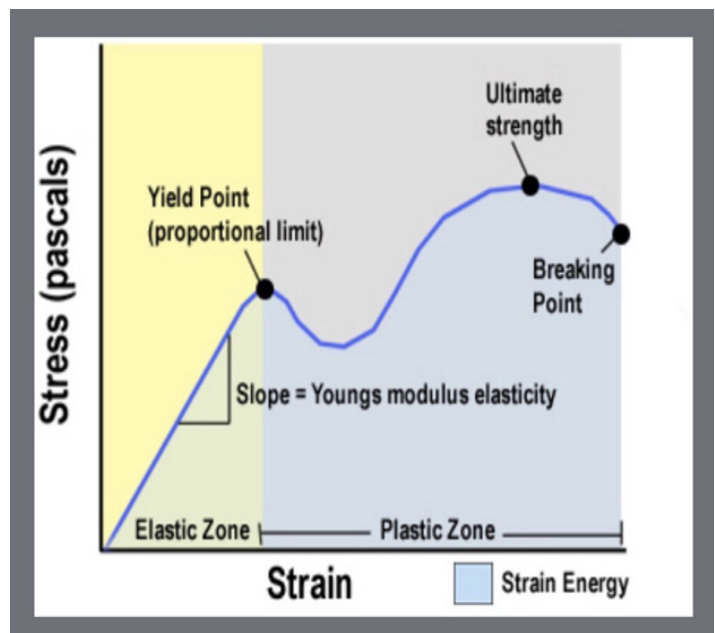


Figure 1: Stress-Strain-Young's modulus, Elastic Zone vs. Plastic Zone

Plasticity

When the force is going beyond the elastic limit of material, it is into a plastic zone which means even when force is removed, the material will not return back to its original state (Figure 1).

Based on various experimental results, the following table lists some Young's modulus associated with different materials:

- Nylon: 2.7 GPa
- Concrete: 17-30 GPa
- Glass fibers: 72 GPa
- Copper: 117 GPa
- Steel: 190-215 GPa
- Diamond: 1220 GPa

Young's modulus in the above table are ranked from soft material (low E) to stiff material (higher E).

Professor James Andrews taught the author linear elasticity at the University of Iowa and Professor Norman Jones taught him non-linear plasticity at Massachusetts Institute of Technology. These two great academic mentors provided him the necessary foundation knowledge to understand these two important subjects in engineering.

Linear Elastic FPG Behavior

In this particular study, he uses the analogy of relationship among stress, strain, and Young's modulus to illustrate a similar relationship between body weight and predicted FPG via a newly defined coefficient of GH.f-modulus, which is listed below:

$$\mathbf{GH.f-modulus = FPG / Weight}$$

$$\mathbf{Young's modulus E = stress / strain}$$

Where FPG is the amount of predicted FPG (note: the predicted FPG can also be replaced by the measured FPG in order to conduct a sensitivity study of FPG behaviors).

Data Collection

Case A (the author) is a 73-year-old male with a 25-year history of T2D. From 7/1/2015 to 10/31/2020 (1,962 days), he has collected 2 data per day, weight and FPG. He utilized these data to conduct his linear elastic FPG behavior research.

In addition, on 5/5/2018, he started to use a continuous glucose monitoring (CGM) sensor device to collect 96 glucose data each day. Within this time period, he uses a sensor device to collect 28 FPG data per day from 00:00 to 07:00 at each 15-minutes time interval. Based on his research, this averaged sensor FPG value is within 1% of margin (i.e., 99% accuracy) from his measured FPG at the wake-up moment using finger piercing and test strip method (Finger FPG).

The period of 7/1/2015 to 10/31/2020 is his "best-controlled" diabetes period, where his average daily glucoses is maintained at 116 mg/dL (<120 mg/dL). He named this as his "linear elastic zone" of diabetes health. Especially, due to his

It should also be noted that in 2010, his average glucose was 280 mg/dL and HbA1C was 10%, while taking three diabetes medications. Please note that the strong chemical interventions from various diabetes medications could seriously alter glucose physical behaviors. He called the period prior to 2015 as his "nonlinear plastic zone" of diabetes health.

The second set of data comes from his wife (Case B) with a 22-

year history of T2D. She began to collect her glucose data via finger-piercing method (finger glucose) since 1/1/2014. On 1/1/2020, she began using the same brand of CGM sensor device to collect her sensor FOG data at the same rate of 28 FPG data per day since 1/1/2020. She discontinued her diabetes medication in 2020.

Case C is 47-year-old male with a BMI over 40 (obesity) and a 4-year history of T2D (new and non-severe diabetes). He started to collect his glucose data using the same model of CGM sensor on 3/18/2020. He has never taken any diabetes medications.

The following lists the different time spans of his four analysis:

- (1) Case A:
From 1/1/2014 to 10/31/2020, every 6 months (semi-annually)
- (2) Case B:
From 1/1/2020 to 10/31/2020, every month (monthly)
- (3) Case C:
From 3/1/2020 to 10/31/2020, every month (monthly)
- (4) Case A, Case B, and Case C
From 3/1/2020 to 10/31/2020, every month (monthly)

He then calculates the value of GH.f-modules by dividing FPG by Weight for each time period. Using the averaged GH.f-modulus as a constant to plug it into the following equation to obtain the predicted FPG.

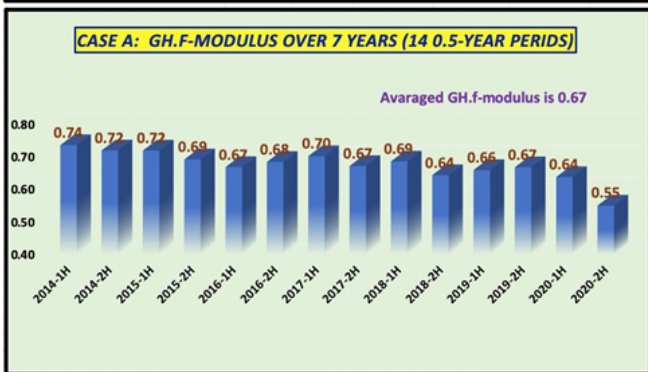
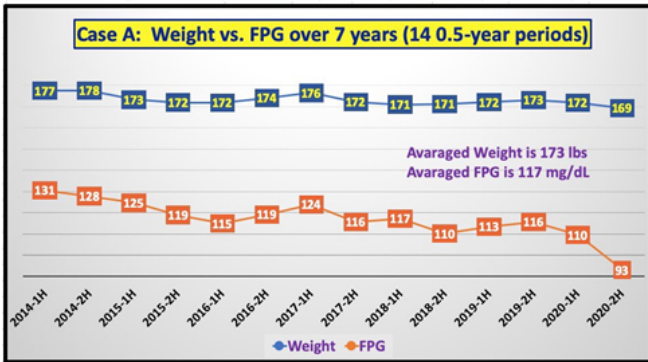
$$\mathbf{Predicted FPG = Weight * GH.f-modulus}$$

Finally, he compared the predicted FPG with the measured FPG to obtain prediction accuracies for each time period.

Results

Figure 2 shows the raw data and the combined two charts; Weight versus FPG and the coefficient of GH.f-modulus, into one diagram for Case A (male patient with 14 semi-annual periods). His average weight is 173 lbs. and average FPG is 117 mg/dL. His average GH.f-modulus is a constant of 0.67 with a variance between 0.55 and 0.74. It should be noted that his significantly lower coefficient of 0.55 in the second half of 2020 is the direct result of his COVID-19 quarantined life. The compatible moving trend (i.e., high correlation) between weight and FPG over these periods is quite obvious. His average predicted FPG using the constant of 0.67 (i.e., a constant GH.f-modulus) is also 117 mg/dL, but with a variance range of FPG prediction error margin between -8% to +5%, excluding significantly positive contribution on his overall health conditions from a stabilized 2020 quarantined lifestyle.

Case A (BMI 25.5)			FPG / Weight		
Periods	Weight	Measured FPG	GH.f-modulus	Predicted FPG	Prediction %
2014-1H	177	131	0.74	120	-8%
2014-2H	178	128	0.72	120	-6%
2015-1H	173	125	0.72	117	-6%
2015-2H	172	119	0.69	116	-3%
2016-1H	172	115	0.67	116	1%
2016-2H	174	119	0.68	117	-2%
2017-1H	176	124	0.70	119	-4%
2017-2H	172	116	0.67	116	0%
2018-1H	171	117	0.69	115	-2%
2018-2H	171	110	0.64	115	5%
2019-1H	172	113	0.66	116	2%
2019-2H	173	116	0.67	117	1%
2020-1H	172	110	0.64	116	6%
2020-2H	169	93	0.55	114	23%
Average	173	117	Average 0.67	117	0%



Case B (BMI 25.8)			FPG / Weight		
Periods	Weight	Measured FPG	GH.f-modulus	Predicted FPG	Prediction %
Jan, 2020	155	108	0.70	104	-4%
Feb, 2020	157	111	0.71	105	-5%
Mar, 2020	157	100	0.64	105	6%
Apr, 2020	155	103	0.66	104	1%
May, 2020	156	108	0.69	105	-3%
Jun, 2020	157	100	0.64	105	5%
Jul, 2020	156	106	0.68	104	-2%
Aug, 2020	155	98	0.63	104	6%
Sept, 2020	154	105	0.68	103	-2%
Oct, 2020	155	105	0.68	104	-1%
Average	155	104	Average 0.67	104	0%

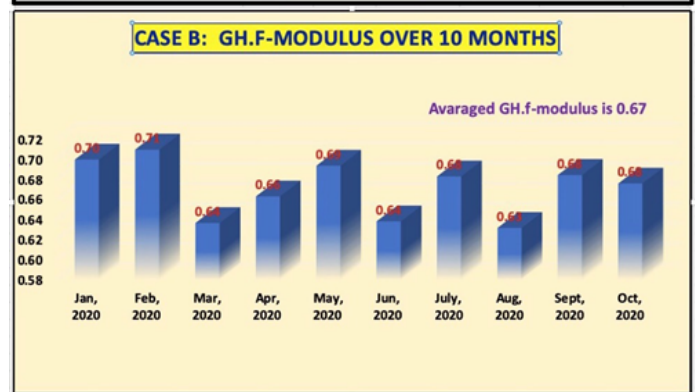
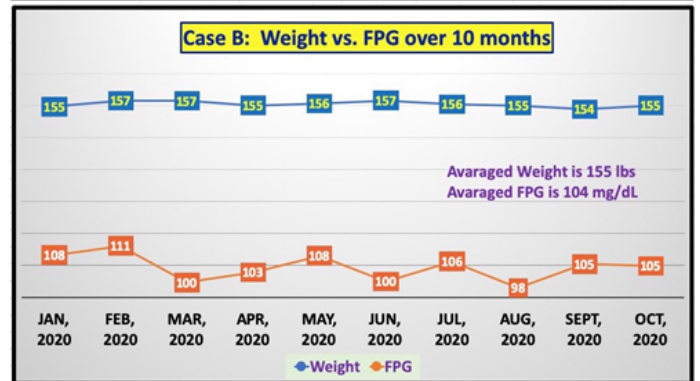


Figure 2: Case A data & charts

Figure 3 depicts the raw data and the combined two charts, Weight versus FPG and the coefficient of GH.f-modulus, into one diagram for Case B (female patient with 10 monthly periods). Her average weight is 155 lbs. and average FPG is 104 mg/dL. Her average GH.f-modulus is a constant of 0.67 as well (same as Case A) with a variance between 0.63 and 0.70. It should be noted that her relatively more evenly distributed GH.f-modulus is due to the relatively smaller changes of her health conditions since 2010 instead of the 7-year-time period for Case A. The compatible moving trend (i.e., high correlation) between Weight and FPG over these 10 months is also quite evident. Her average predicted FPG using the constant of 0.67 (i.e., a constant GH.f-modulus) is also 104 mg/dL, but with a variance range of FPG prediction error margin between -5% to +6%.

Figure 3: Case B data & charts

Figure 4 illustrates the raw data and the combined two charts, Weight versus FPG and the coefficient of GH.f-modulus, into one diagram for Case C (younger male patient with 8 monthly periods). His average weight is 292 lbs. (extremely obese) and average FPG is 105 mg/dL (similar to Case B). His average GH.f-modulus is a constant of 0.36 due to his obesity, with a variance between 0.34 and 0.40. The compatible moving trend (i.e., high correlation) between Weight and FPG over these 8 months is also quite obvious. It should be highlighted that he has reduced his monthly average weight from 301 lbs. in January 2020 to 273 lbs. in October 2020. This significant weight reduction effort has assisted him with his average FPG reduction from 120 mg/dL in March 2020 to 95 mg/dL in October 2020. His average predicted FPG using the constant of 0.36 (i.e., a constant GH.f-modulus) is also 105 mg/dL,

but with a variance range of FPG prediction error margin between -9% to +5%.

Case C (BMI 40.7)	lbs	mg/dL	Periods	FPG / Weight	Predicted FPG	Prediction %
Mar, 2020	301	120	Mar, 2020	0.40	109	-9%
Apr, 2020	299	107	Apr, 2020	0.36	108	1%
May, 2020	300	105	May, 2020	0.35	108	3%
Jun, 2020	299	105	Jun, 2020	0.35	108	3%
Jul, 2020	296	107	July, 2020	0.36	107	0%
Aug, 2020	288	108	Aug, 2020	0.38	104	-4%
Sept, 2020	281	97	Sept, 2020	0.34	101	5%
Oct, 2020	273	95	Oct, 2020	0.35	99	4%
Average	292	105	Average	0.36	105	0%

BMI 25.5	lbs	mg/dL	BMI 25.5	FPG / Weight	BMI 25.8	lbs	mg/dL	BMI 25.8	FPG / Weight	BMI 40.7	lbs	mg/dL	BMI 40.7	FPG / Weight
Case A:	Weight	FPG	Case A:	GH.f-modulus	Case B:	Weight	FPG	Case B:	GH.f-modulus	Case C:	Weight	FPG	Case C:	GH.f-modulus
Mar, 2020	172	108	Mar, 2020	0.63	Mar, 2020	157	100	Mar, 2020	0.64	Mar, 2020	301	120	Mar, 2020	0.40
Apr, 2020	172	113	Apr, 2020	0.66	Apr, 2020	155	103	Apr, 2020	0.66	Apr, 2020	299	107	Apr, 2020	0.36
May, 2020	173	100	May, 2020	0.58	May, 2020	156	108	May, 2020	0.69	May, 2020	300	105	May, 2020	0.35
Jun, 2020	172	100	Jun, 2020	0.58	Jun, 2020	157	100	Jun, 2020	0.64	Jun, 2020	299	105	Jun, 2020	0.35
Jul, 2020	170	99	July, 2020	0.56	Jul, 2020	156	106	July, 2020	0.68	Jul, 2020	296	107	July, 2020	0.36
Aug, 2020	171	99	Aug, 2020	0.58	Aug, 2020	155	98	Aug, 2020	0.63	Aug, 2020	288	108	Aug, 2020	0.38
Sept, 2020	169	100	Sept, 2020	0.59	Sept, 2020	154	105	Sept, 2020	0.68	Sept, 2020	281	97	Sept, 2020	0.34
Oct, 2020	167	99	Oct, 2020	0.56	Oct, 2020	155	105	Oct, 2020	0.68	Oct, 2020	273	95	Oct, 2020	0.35
Average	171	101	Average	0.59	Average	155	103	Average	0.66	Average	292	105	Average	0.36

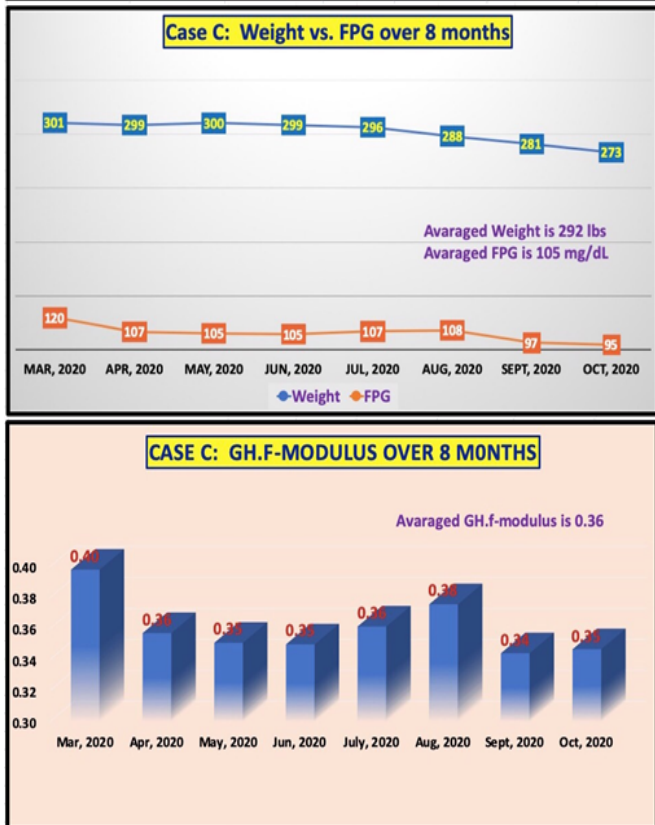


Figure 4: Case C data & charts

Figure 5 reflects the results of a special analysis by using a consistent time (monthly data from 3/1/2020 to 10/31/2020) for Cases A, B, and C. The key objective of conducting this timeframe analysis is to compare their GH.f-modulus over the same 8-month-time frame.

Listed below are the values of the GH.f-modulus for each patient over the 8-month period in 2020, which are listed in the order of (Case A, Case B, and Case C):

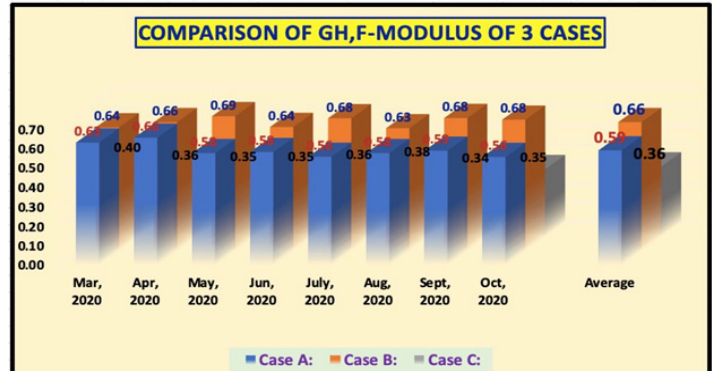


Figure 5: GH.f-modulus during the consistent 8-month time span of Cases A, B, and C

- March 2020: (0.63, 0.64, 0.40)
- April 2020: (0.66, 0.66, 0.36)
- May 2020: (0.58, 0.69, 0.35)
- June 2020: (0.58, 0.64, 0.35)
- July 2020: (0.56, 0.68, 0.36)
- August 2020: (0.58, 0.63, 0.38)
- September 2020: (0.59, 0.68, 0.34)
- October 2020: (0.56, 0.68, 0.35)

Average GH.f: (0.59, 0.66, 0.36)

Although the coefficient changes from month to month, the magnitude of its changes are not significant. The results for Case C is the same as in Figure 4, but the results for Case B is smaller than in Figure 3 due to a shorter 8-month period used. The most significant difference is for Case A. The 14 semi-annual analysis has an average GH.f-modulus of 0.67, while his 8-month analysis has an average GH.f-modulus of 0.59. The 12% difference is a result from the different time spans chosen, which demonstrate the characteristics of organic blood material. There are more sources of influences than blood alone. In reality, weight and glucose are involved with many internal organs and hormones produced by the body.

Discussion

Patients with varying chronic diseases would have different coefficient of GH.f-modulus. Both Case A and Case B are long-term T2D patients; however, their weights are still within the boundary of normal and slightly overweight with BMI around 25. Therefore, using 14 semi-annual periods for Case A and 10 months for Case B, their coefficients are the same at 0.67. However, due to Case A's stringent lifestyle management to control his diabetes, his weight and glucoses, including FPG, have reduced significantly, especially in 2020 where his coefficient became 0.59 in comparison with Case B's 0.66.

Case C is another story. His extreme-obese condition (BMI at

40.7) is much more serious than his diabetes conditions with 4 years of short history. In order to compensate for his heavy weight, he must have a much lower value of the GH.f-modulus (his coefficient of 0.36 is at 54% level of 0.67 for both Case A and Case B) in order to match with his measured FPG level at 105 mg/dL (normal glucose level).

At first glance of this coefficient, it appears that it as a variable, rather than a constant. However, by examining their values within a reasonable time span, they do not vary that much. That is why it is called a “pseudo-linear” relationship. Once we have collected sufficient data for a particular time period, we can then easily figure out the suitable coefficients for both FPG and PPG respectively, i.e. GH.f-modulus and GH.p-modulus, to be used in glucose predictions.

Conclusions

The article represents the author’s special interest in using math-physical and engineering modeling methodologies to investigate various biomedical problems. The methodology and approach are a result of his specific academic background and various professional experiences prior to the start of his medical research work in 2010. Therefore, he has been trying to link his newly acquired biomedical knowledge over the past decade with his previously acquired knowledge of mathematics, physics, computer science, and engineering for over 40 years.

The human body is the most complex system he has dealt with, which includes aerospace, navy defense, nuclear power, computers, and semiconductors. By applying his previous acquired knowledge to his newly found interest of medicine, he can discover many hidden facts or truths inside the biomedical systems. Many basic concepts, theoretical frame of thoughts, and practical modeling techniques from his fundamental disciplines in the past can be applied to his medical research endeavor. After all, science is based on theory from creation and proof via evidence, and as long as we can discover hidden truths, it does not matter which method we use and which option we take. This is the foundation of the GH-Method: math-physics medicine.

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Acknowledgement

Foremost, I would like to express my deep appreciation to my former professors: professor James Andrews at the University of Iowa, who helped develop my foundation in basic engineering and computer science, and Professor Norman Jones at the Massachusetts Institute of Technology, who taught me how to solve tough scientific problem through the right attitude and methodology.

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