

Viscoelastic or Viscoplastic Glucose Theory (VGT #145): Energy Analyses of Different Postprandial Plasma Glucose Waveforms and Data from a Total of 8,488 Meals which Includes 5,801 Healthy-Level Meals, 1,968 Pre-Diabetes Level Meals, and 719 Diabetes-Level Meals over 7+ Years from 5/1/2015 to 9/10/2022 and Utilizing 3 Different Energy Analysis Methods and Tools of Time Domain, Space Domain, and Frequency Domain of the GH-Method: Math-Physical Medicine (No. 737)

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Introduction

This research report is the author's second written article which is 100% dependent on his developed VGT software tool. There are 2 prominent findings: First, if excluding the meal number influence (the data quantity %), the space-domain (SD) energy contribution or degree of influence from these 3 selected postprandial plasma glucose (PPG) levels are:

Healthy (0-119 mg/dL) = 29%
Pre-T2D (120-139 mg/dL) = 33%
T2D (140-500 mg/dL) = 38%

Second, if including the meal number influence (the data quantity %), the SD energy contribution or degree of influence from these 3 selected PPG levels are:

Healthy (0-119 mg/dL) = 64%
Pre-T2D (120-139 mg/dL) = 25%
T2D (140-500 mg/dL) = 10%

The derived conclusion is that we should avoid having hyperglycemic situations. If we do have high post-meal glucose levels, they should be limited to a minuscule group of meals.

The author has consumed a total of 8,488 meals (PPG within 0-500 mg/dL with 13.7 grams of average carbs/sugar) during 7+ years from 5/1/2015 to 9/10/2022 that include 5,801 healthy levels of PPG (0-119 mg/dL with 10.3 grams of average carbs/sugar), 1,968 pre-T2D level of PPG (120-139 mg/dL with 16.4 grams of average carbs/sugar), and 719 T2D level of PPG (140-500 mg/dL with 37.5 grams of averaged carbs/sugar). It should be noted that all of the meals have average post-meal walking

steps of around 4,000 steps.

Other than the observation and research on the PPG amplitude difference (outlined in Figure 3), he also wondered **what the energy differences caused by the three different PPG levels (3 input causes) on their total PPG level (1 output symptom), particularly utilizing 3 different energy tools of time domain (TD), space domain (SD), and frequency domain (FD).**

From the practical viewpoint of diabetes control, he can discover additional information regarding the impact on his PPG resulting from the three different PPG levels from thousands of different meals during the past 7+ years. He can then apply what he has learned from this research study to further reduce his average PPG, daily estimated average glucose (eAG), and hemoglobin A1C (HbA1C) level which can assist in the continuous daily efforts of his type 2 diabetes (T2D) control. **More importantly, by knowing the quantitative degree of damage to his internal organs from various PPG-associated energy, he would be able to estimate the damage levels within various periods due to the hyperglycemic situations, e.g. high PPG, and their associated high energies.**

In this article, he has utilized two analysis cases. The first is the **inclusion** of the data quantity (meals number percentages) and the second is the **exclusion** of the data quantity (meals number percentages). **This inclusion or exclusion of "data quantity" in the normalization process of SD-VGT analysis would result in vastly different energy results which need some explanation. However, it indeed offers useful interpretation and indicators from the energy results.**

The normalization factor of “without meals number %” is dividing the PPG values by 120 mg/dL, while the normalization factor of “with meals number %” is dividing the PPG values by (120 / meals data %). For example, for the case of “with meal numbers”, these 3 distinctive normalization factors are:

healthy PPG = / 1.757 (= 120/68.3)

Pre-T2D = / 5.172 (= 120/23.2)

T2D = / 14.118 (= 120/8.5)

Furthermore, his developed equation for *the predicted total PPG “with meals number percentages”* is listed as:

Predicted PPG based on SD hysteresis loop areas (for the case of with meal #)

*= (Healthy PPG value * SD Healthy PPG energy ratio of 64% + Pre-T2D PPG value * SD Pre-T2D PPG energy ratio of 25% + T2D PPG value * SD T2D PPG energy ratio of 10%)*

For simplicity, he only presents the predicted PPG using the case of “with meal %” in this article. Therefore, he can calculate the prediction accuracy of measured PPG versus predicted PPG as follows:

Methods

The Author’s Case of Diabetes and Complications

The author has been a severe T2D patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time with a one-time glucose reading of 380 mg/dL. By 2010, he still weighed 198 lb. (BMI 29.2) with average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached 1161b (hyperlipidemia) and albumin-creatinine ratio (ACR) at 116 (kidney issues). He also suffered from five cardiac episodes within a decade from 1993 through 2003 caused by work stress and diabetes. In 2010, three independent physicians warned him about his urgent need for kidney dialysis treatment and the risk of his life-threatening health situation such as dying from his severe diabetic complications. Other than the cerebrovascular disease (stroke), he has suffered many known diabetic complications, including both macro-vascular & micro-vascular complications, nerve damage as in retinopathy and foot ulcer, as well as a hormonal disturbance, e.g. hypothyroidism.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition to save his own life. After developing the metabolism model in 2024, during 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and A1C. As a result, from using his developed mathematical metabolism index (MI) model in 2014 and the 4 prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg, BMI 32.5) to 176 lbs. (89 kg, BMI 26.0), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger glucose reading from 250 mg/dL to 120 mg/dL, and lab-tested A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications as of 12/8/2015.

Around that time (2014-2017), he started to focus on preventive medicine instead of blindly trusting and depending on medication treatments only. He also gambled on his belief that

most human organs have strong inherent abilities to self-repair themselves through lifestyle improvements by taking good care of them - even though it can only accomplish a certain degree of repairing or healing dependent on certain organ cells and their status of damage, such as pancreatic beta cells.

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 dining out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolic impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control and overall metabolism state were somewhat affected during this two-year heavy traveling period.

Since 1/19/2020, living in a COVID-19 quarantined lifestyle, not only has he written and published ~500 medical papers in 100+ journals, but he has also reached his best health conditions in the past 26 years. By the beginning of 2022, his weight was further reduced to **168 lbs. (BMI 24.8) along with a 5.8% A1C value (beginning level of pre-diabetes)**, without having any medication interventions or insulin injections. During the period from 1/1/2022 to 8/20/2022, his average FPG is 93 mg/dL, PPG is 113 mg/dL, and daily glucose is 106 mg/dL. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, the accumulated knowledge of chronic diseases, various complications, practical lifestyle management experiences, and development of many high-tech tools along with his medical research academic findings have contributed to his excellent health status since 1/19/2020, the beginning date of his self-quarantined life.

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 the present day. In his research work, he uses his CGM sensor glucose at a time interval of 15 minutes (96 data per day). Incidentally, *the average sensor glucoses between 5-minute intervals and 15-minute intervals has only a 0.6% difference (average glucose of 111.86 mg/dL for 5 minutes and average glucose of 111.18 mg/dL for 15 minutes with a correlation of 94% between these two sensor glucose curves)* during the period from 2/19/20 to 7/22/22.

Therefore, over the past 13 years, he could study and analyze his collected 3+ 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 research work has a goal of achieving both “high precision” and “quantitative proof” in the medical findings for the ultimate objectives of “preventive medicine”.**

The following timetable provides a rough sketch of the emphasis in his medical research during each stage:

- 2000-2013: Self-study diabetes and food nutrition, developing a data collection and analysis software.

- 2014: Develop a mathematical model of metabolism, using engineering modeling and advanced mathematics.
- 2015: Weight & FPG prediction models, using neuroscience.
- 2016: PPG & HbA1C prediction models, using optical physics, artificial intelligence (AI), and neuroscience.
- 2017: Complications due to macro-vascular research, such as cardiovascular disease (CVD), coronary heart diseases (CHD), and stroke, using pattern analysis and segmentation analysis.
- 2018: Complications due to micro-vascular research such as kidney (CKD), bladder, foot, and eye issues (DR).
- 2019: CGM big data analysis, using wave theory, energy theory, frequency domain analysis, quantum mechanics, and AI.
- 2020: Cancer, dementia, longevity, geriatrics, DR, hypothyroidism, diabetic foot, diabetic fungal infection, and linkage between metabolism and immunity, learning about certain infectious diseases, such as COVID-19.
- 2021: Applications of linear elastic glucose theory (LEGT) and perturbation theory from quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia.
- 2022: Applications of viscoelastic/viscoplastic glucose theory (LEGT) on 128 biomedical research cases and 5 economics research cases.

Again, to date, he has spent ~40,000 hours self-studying and researching medicine and he has read 3,000+ published medical papers online. He has collected and calculated more than three million pieces of data regarding his own medical conditions and lifestyle details. In addition, he has written and published 700+ medical research papers in 100+ various medicine, physics, mathematics, and engineering journals. Moreover, he has also given 120+ presentations at 70+ international medical conferences. He has continuously dedicated his time (11-12 hours per day and work each day of a year, without rest during the past 13 years) and efforts to his medical research work and shared his findings and learnings with other patients worldwide. In addition, he has also spent the past 12 years developing and maintaining a medicine and health software APP on his iPhone which functions as his private numerical laboratory to process the various experimental datasets of his medical conditions and lifestyle details.

Brief Introduction of Math-Physical Medicine (MPM) Research

The author has collected 3+ million pieces of data regarding his health condition and lifestyle details over the past 13 years. He spent the entire year of 2014 developing a metabolism index (MI) model using a topology concept, nonlinear algebra, algebraic geometry, and finite element method. This MI model contains various measured biomarkers and recorded lifestyle details along with their induced new biomedical variables for an additional ~1.5 million data. Detailed data of his body weight, glucose, blood pressure, heart rate, blood lipids, body temperature, and blood oxygen level, along with important lifestyle details, including diet, exercise, sleep, stress, water intake, and daily life routines are included in the MI database. In addition, these lifestyle details also include some lifetime bad habits and certain environmental exposures. Fortunately, the author has none of these lifetime bad habits and an extremely low degree of exposure to

environmental factors. The developed MI model has a total of 10 categories covering approximately 500 detailed elements that constitute his defined “metabolism index model” which are the building blocks or root causes for diabetes and other chronic disease induced complications, including but not limited to CVD, CHD, stroke, CKD, DR, neuropathy, foot ulcer, hypothyroidism, dementia, and various cancers. The end result of the MI development work is a combined MI value within any selected period with 73.5% as its dividing line between a healthy and unhealthy state. The MI serves as the foundation for many of his follow-up medical research work.

During the period from 2015 to 2017, he focused his research on type 2 diabetes (T2D), especially glucose, including fasting plasma glucose (FPG), PPG, estimated average glucose (eAG), and hemoglobin A1C (HbA1C). During the following period from 2018 to 2022, he concentrated on researching medical complications resulting from diabetes, chronic diseases, and metabolic disorders which include heart problems, stroke, kidney problems, retinopathy, neuropathy, foot ulcer, diabetic skin fungal infection, hypothyroidism, diabetic constipation, dementia, and various cancers. He also developed a few mathematical risk models to calculate the probability percentages of developing various diabetic complications based on this MI model. From his previous medical research work with 700+ published papers, he has identified and learned that ***the associated energy of hyperglycemic conditions is the primary source of causing many diabetic complications which lead to death.*** Therefore, a thorough knowledge of these energies is important for achieving a better understanding of the dangerous complications.

TD, SD, and FD Analysis Tools

This section has brief descriptions of TD correlation analysis with other observational results, SD VGT analysis with hysteresis loop area’s energy results, and FD analysis with frequency curve area’s energy results.

First of all, by using a TD analysis tool, we can examine the curves’ moving trend and pattern visually along with their correlation numerically. We can also study the extremely high or low data values in the dataset. The visual observation or calculation-derived interpretations are a part of statistical analysis results which can indeed provide some useful hints or even derive some accurate conclusions. However, we must be aware of the limitations of the selected data size and time window and also be cautious of the appropriate statistics tool we choose.

Regarding the TD energy, we can apply the rudimentary definition of physics that ***“the wave carried energy is directly proportional to the square of wave’s amplitude”***. However, the data quantity % of each wave category should be considered and included to obtain a more accurate TD energy value.

The author would like to describe the essence of his developed “hybrid model” that combines both the SD viscoelastic/plastic VGT analysis method and FD FFT analysis method with a comparison against the traditional TD statistical correlation analysis.

It is described in 10 steps in the English language instead of using mathematical equations to explain it. In this article, he has applied both the SD-VGT operations (steps 1-7) and the FD-FFT operations (steps 8-10). As a result, it is aimed at readers who do not have an extensive background in those academic subjects of engineering, physics & mathematics.

The first step is to collect the output data or symptom (strain or ϵ) on a time scale. The second step is to calculate *the output change rate with time ($d\epsilon/dt$)*, i.e. the change rate of strain or symptom over each period. The third step is to gather the input data or cause (*viscosity or η*) on a time scale. The fourth step is to calculate the time-dependent input or cause (*time-dependent stress or σ*) by multiplying $d\epsilon/dt$ and η together. The “time-dependent input or cause equation” of “*stress $\sigma =$ strain change rate of $d\epsilon/dt *$ viscosity η* ” is the essential part of this “time dependency”. The fifth step is to plot the input-output (i.e. stress-strain or cause-symptom) curve in a two dimensional space-domain or SD (x-axis versus y-axis) with strain (output or symptom) on the x-axis and stresses (time-dependent inputs, causes, or stresses) on the y-axis.

The sixth step is to calculate the total enclosed area within these stress-strain curves or input-output curves (i.e. the hysteresis loops), which is also an indicator of associated energies (either created energy or dissipated energy) of this input and output dataset. These energy values can also be considered as the degrees of influence on output by inputs. The seventh step is the assembly of the area values of the selected periods to compare the “historical progression and contribution of medical condition” over certain time periods.

For the frequency domain, the eighth step is to define a “hybrid input variable” by using “*strain*stress*” which yields another accurate estimation of energy ratio similar to the SD-VGT energy ratio associated with the hysteresis loop. The ninth step is to present these hybrid models’ results of (strain*stress) in TD and then perform the FFT operation to convert them into FD. The enclosed area of the frequency curve (where the x-axis is the frequency and the y-axis is the amplitude of energy) can be used to estimate the total FD-FFT energy. The tenth step is to compare these FD energy results against the SD-VGT energy results, or even TD energy results.

After providing the above 10-step description, the author would still like to use the following set of VGT stress-strain mathematical equations in a two-dimensional SD to address the selected medical variables:

Strain

= ϵ (*time-dependency characteristics of individual strain value at the present time duration*)

Stress

= σ (*based on the change rate of strain multiplying with a chosen viscosity factor η*)

= $\eta * (d\epsilon/dt)$

= $\eta * (d\text{-strain}/d\text{-time})$

= (*viscosity factor η using individual viscosity factor at present time duration*) * (*strain at present quarter - strain at previous time duration*)

Some of these inputs (causes or viscosity factors) are further normalized by dividing them or being divided by a normalization factor using certain established health standards or medical pieces of knowledge. Some examples of normalization factors are 6.0 for HbA1C, 120 mg/dL for glucose, 25 for body mass index (BMI), 4,000 steps after each meal, 10,000 or 12,000 steps for daily walking exercise depending on time-period selection, 13 grams to 20 grams of carbs/sugar intake amount per meal depends on time-period selection. If using the originally collected data, i.e. the non-normalized data would distort the numerical comparison of the hysteresis loop areas. Using this “normalization process”, we can remove the dependency of the individual unit or certain unique characteristics associated with each viscosity factor. This process allows us to convert the originally collected variables into a set of “*dimensionless variables*” for easier numerical comparison and result interpretation.

*The normalization factor for the “without meals number” is divided by the egg meal PPG by 120 mg/dL, while the normalization factor for the “with meals number” is divided by the egg meal PPG by (120*egg meal number percentages).*

Results

Figure 1 shows the background information regarding meals numbers, carbs/sugar grams, and post-meal walking steps for each PPG level of meals - with the input data panel of his VGT software on the iPhone.



Figure 1: Background information and data input panel of VGT software

Figure 2 depicts 2 data table for both “no data %” and “with data %”.

Type	Total PPG	Healthy PPG	Pre-T2D PPG	T2D PPG
Meal #	8488	5801	1968	719
Data %	100%	68%	23%	8%
9/11/22	PPG Level	0-119	120-139	140-500
No Data %	Total PPG	Healthy PPG	Pre-T2D PPG	T2D PPG
		N. 1	N. 2	N. 3
	Strain Rate	Strain	Stress 1	Stress 2
		Stress 3	Height 1	Height 2
		Height 3	Area 1	Area 2
		Area 3	Time-Zone	FD 1
		FD 2	FD 3	
First-Bite	121	119	128	136
15 min	123	121	131	140
30 min	128	124	137	148
45 min	131	127	142	156
60 min	131	126	145	163
75 min	129	123	144	167
90 min	126	120	142	169
105 min	123	116	141	171
120 min	120	113	139	170
135 min	120	113	138	171
150 min	121	115	137	169
165 min	121	115	137	167
180 min	121	116	136	161
Avg / Sum	124	119	138	161
Correlation	100%	95%	62%	-9%
TD Energy	60074	14113	19068	29573
TD Energy	TD Ratio	24%	32%	44%

Type	Total PPG	Healthy PPG	Pre-T2D PPG	T2D PPG
Meal #	8488	5801	1968	719
Data %	100%	68%	23%	8%
9/11/22	PPG Level	0-119	120-139	140-500
With Data %	Total PPG	Healthy PPG	Pre-T2D PPG	T2D PPG
		N. 1	N. 2	N. 3
	Strain Rate	Strain	Stress 1	Stress 2
		Stress 3	Height 1	Height 2
		Height 3	Area 1	Area 2
		Area 3	Time-Zone	FD 1
		FD 2	FD 3	
First-Bite	121	119	128	136
15 min	123	121	131	140
30 min	128	124	137	148
45 min	131	127	142	156
60 min	131	126	145	163
75 min	129	123	144	167
90 min	126	120	142	169
105 min	123	116	141	171
120 min	120	113	139	170
135 min	120	113	138	171
150 min	121	115	137	169
165 min	121	115	137	167
180 min	121	116	136	161
Avg / Sum	124	119	138	161
Correlation	100%	95%	62%	-9%
TD Energy	60074	14113	19068	29573
TD Energy	TD Ratio	24%	32%	44%

Figure 2: 2 Data tables

Figure 3 displays 1 TD-squared PPG analysis results.

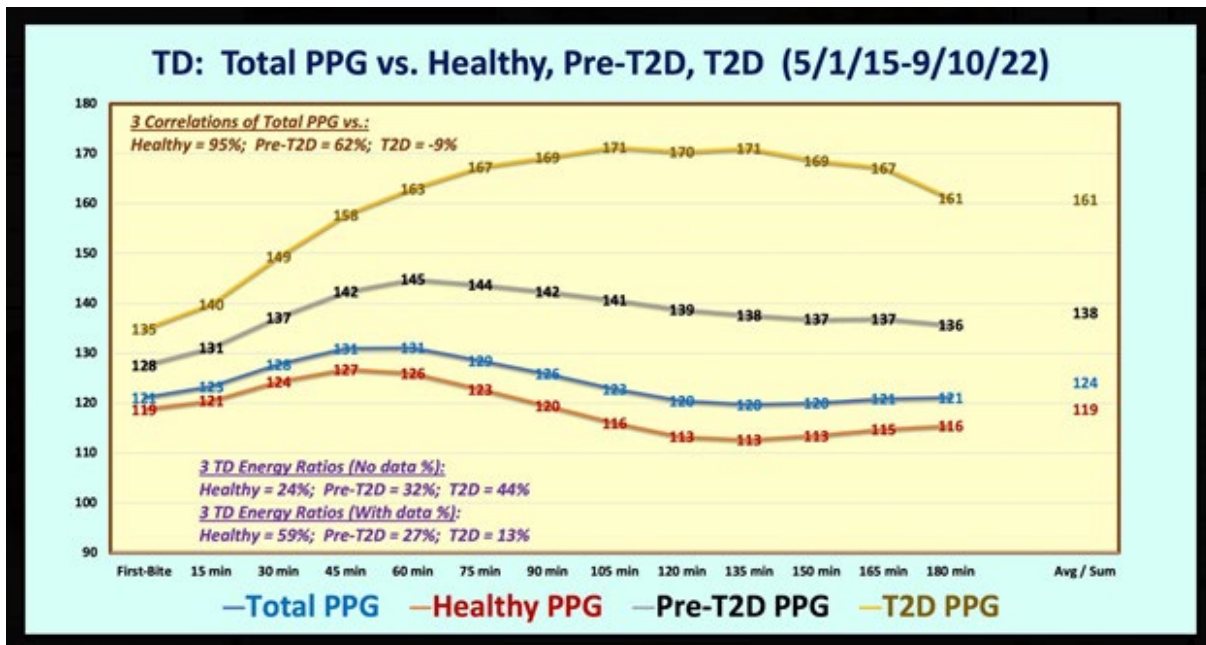


Figure 3: Time-domain result

Figure 4 reflects 2 SD graphic diagrams and their energy analysis results.

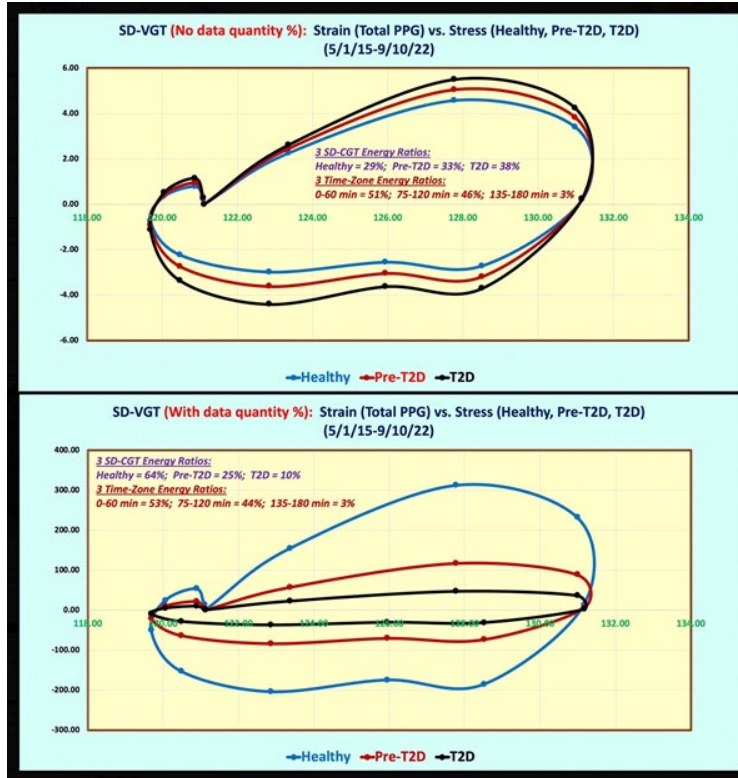


Figure 4: 2 space-domain VGT analysis results

Figure 5 reveals 2 FD-FFT energy analysis results.



Figure 5: 2 frequency-domain analysis results

Figure 6 illustrates the comparison of the combined total PPG curve against the predicted PPG curve (using the case of with meals number %).

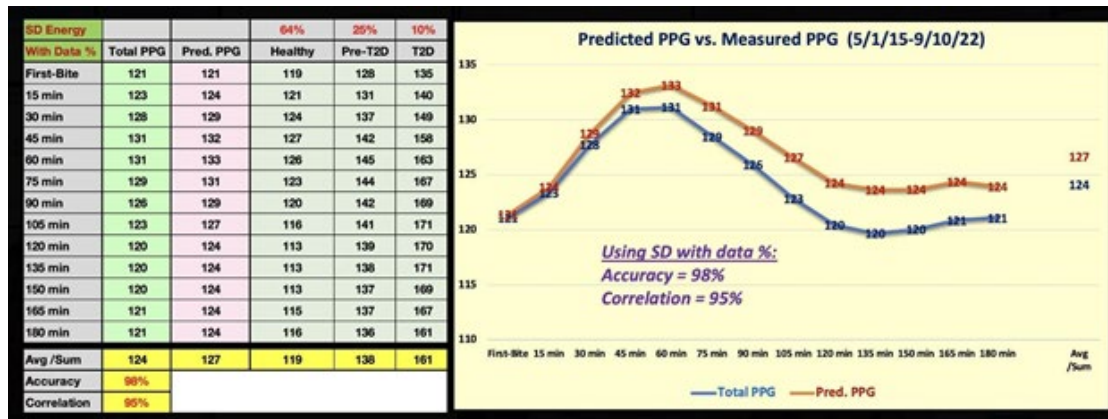


Figure 6: Comparison of predicted total PPG versus measured total PPG

Conclusions

In summary, there are 5 observations listed below regarding *the total PPG versus healthy PPG, Pre-T2D PPG, and T2D PPG*.

(1) Of the three PPG waveforms in TD, the 3-hour T2D meals PPG waveform shows a “Himalaya mountain” shape, while the other two 3-hour PPG waveforms reflect a kind of “low rolling-hill” shape. The average PPG over the 3-hour values are: healthy = 119 mg/dL, Pre-T2D = 138 mg/dL, T2D = 161 mg/dL with the total averaged PPG = 124 mg/dL. Other than the simple statistical observations, more importantly, his squared PPG energy ratio for the case “without meal number” are: healthy = 24%, Pre-T2D = 32%, T2D = 44%. This is due to the average PPG values being ranked as: T2D > Pre-T2D > Healthy. However, his squared PPG energy ratio for the case “with meal number” are: healthy = 59%, Pre-T2D = 27%, T2D = 13%. This is due to the meals number % are: healthy (68%) > Pre-T2D (23%) > T2D (8%).

(2) Applying the SD viscoelastic or viscoplastic glucose (SD-VGT) energy tool, both of the two diagrams of hysteresis loops (with and without data %) have presented “viscoelastic” behavior. Furthermore, the energy ratios for the case of “without meal data %” are: healthy = 29%, Pre-T2D = 33%, T2D = 38%. This is due to the average PPG values being ranked as: T2D > Pre-T2D > Healthy. However, the energy ratios for the case of “with meal data %” are: healthy = 64%, Pre-T2D = 25%, T2D = 10%. This is due to the meals number percentages as: healthy (68%) > Pre-T2D (23%) > T2D (8%). In addition, the three time-period energy ratios for without meal number case and with meal number case are almost identical: 0-min to 60-min at 51% to 53%, 60-min to 120-min at 44% to 46%, and 120-min to 180-min at 3%. This shows that from the viewpoint of energy generation and energy dissipation, the first hour’s generated energies are almost totally dissipated during the second hour.

(3) Applying the FD-FFT energy tool and using a new variable of (strain*stress) from SD, his FD-FFT energy ratios for the case of “without meal data %” are: healthy = 25%, Pre-T2D = 33%, T2D = 43%; while for the case of “with meal data %” are: healthy = 85%, Pre-T2D = 13%, T2D = 2%.

(4) The above energy ratios using the 3 different methods are comparable to each other. However, the author prefers the SD-VGT method since it has very sound theoretical support. The

TD square-amplitude approach can provide a kind of “quick but not so dirty” result due to its rudimentary definition. The FD-FFT analysis can indeed provide “somewhat amplified” results due to the author’s defined FD variable as the (strain*stress).

(5) As a comparison of the predicted total PPG versus measured total PPG for the case of “with meal number influence” has produced an extremely high prediction accuracy (98%) and correlation coefficient (95%).

From the viewpoint of associated energy, the author could apply his learned knowledge from this article to better control the overall glucose situation by avoiding unhealthy hyperglycemic situations from high amounts of carbs/sugar consumption in his daily meals.

References

For editing purposes, the majority of the references in this paper, which are self-references, have been removed for this article. Only references from other authors' published sources remain. The bibliography of the author’s original self-references can be viewed at www.eclaircmd.com.

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For reading more of the author’s published VGT or FD analysis results on medical applications, please locate them through three published special editions from the following three specific journals:

- (1) Series of Endocrinology, Diabetes and Metabolism (contact: Patrick Robinson).
- (2) Journal of Applied Material Science & Engineering Research (contact: Catherine).
- (3) Advances in Bioengineering and Biomedical Science Research (contact: Sony Hazi).

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