

The GH-Method

Viscoelastic and Viscoplastic Glucose Theory (VGT #127): A Sensitivity Study of Normalization Factors Using Three Different Energy Methods, Time Domain, Space Domain, and Frequency Domain, to Calculate Energies or Degrees of Influence on the US Total Postprandial Plasma Glucose versus US Home-Cooked Meals, US Restaurant Meals, and Airline Meals Over 4+ Years from 5/8/2018 to 8/11/2022 Based on Math-Physical Medicine Method (No. 718)

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Abbreviations: FFT: fast Fourier transform; T2D: type 2 diabetes; PPG: postprandial plasma glucose; FPG: fasting plasma glucose; FD: frequency domain; SD: space domain; TD: time domain; MPM: math-physical medicine

1. INTRODUCTION

The author has conducted medical research work using viscoelastic or viscoplastic glucose theory (VGT) starting on 1/8/2022 with Paper No. 578. During his research period, he has written 126 papers where he learned in depth the subtlety and things to watch out for by applying this specific research tool.

In the beginning, he selected multiple input viscosities without using any normalization factors (NF); therefore, he obtained some enlarged or dwindled stress components due to differences in their originally inherited measurement units. Afterward, he learned that some meaningful NF values should be used before calculating the hysteresis loop areas of the stress-strain diagram, i.e. input causes versus output symptoms diagram for the biomedical studies. Sometimes, NF values are used in reverse, such as using 120 mg/dL divided by glucose values or utilizing 4,000 steps divided by the post-meal walking steps. This is due to the glucose unit following the pattern of lower the better whereas exercise is more the better.

In this research article, he studies the contribution of energy (or degree of influence) of postprandial plasma glucose (PPG) on the total of 3,557 US meals from 3,290 US home-cooked meals, 183 US restaurant or cafe meals, and 84 airlines-prepared meals. The mathematical ratio of meal number distribution is "92% : 5% : 2%". It should be mentioned that there are 148 meals from franchised chain restaurants, such as McDonald's and 18 prepared meals by various supermarkets that are not included in this analysis due to the limitation of input data selection and concerns of processed data complications.

As a result, he thought about only using 120 mg/dL (break-even line of diabetes) to divide the PPG values which would provide the energy contribution results from each type of meal, such as "airline energy 23% to 28% > cafe energy 36% to 37% > home-cooked energy 36% to 39%". These calculated energies revealed the PPG characteristics resulting from each meal "type".

However, these types of calculated energy contributions are missing the “overall impact on the total PPG from each meals group by including influences from meal numbers”. Therefore, he inserted another set of energy calculations using a modified NF value of $NF = (\text{input}/120) * (\text{meal numbers distribution } \%)$ to conduct the same energy analyses via both SD-VGT and FD-FFT. Under this additional “influence of meal numbers percentages”, the newly calculated energy contribution results are: “home-cook energy 90% to 99.5% > cafe energy 0.4% to 7% > airline energy 0.1% to 3%”. This set of calculated energies uncovered the specific influences from “meal numbers”.

2. METHODS

2.1 Brief introduction of math-physical medicine (MPM) research

The author has collected 3+ million 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 essential 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 cardiovascular disease (CVD), chronic heart disease (CHD), stroke, chronic kidney disease (CKD), diabetic retinopathy (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 vital for achieving a better understanding of the dangerous complications.

2.2 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.

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 fast Fourier transform (FFT) analysis method together with a comparison against the traditional time-domain 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 $\sigma = \text{strain change rate of } d\epsilon/dt * \text{viscosity } \eta$ ” 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 assembling 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 a time domain and then perform the fast Fourier transformation (FFT) operation to

convert them into a frequency domain. 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
 $= \epsilon$ (time-dependency characteristics of individual strain value at the present time duration)

Stress
 $= \sigma$ (based on the change rate of strain multiplying with a chosen viscosity factor η)
 $= \eta * (d\epsilon/dt)$
 $= \eta * (d\text{-strain}/d\text{-time})$
 $= (\text{viscosity factor } \eta \text{ using individual viscosity factor at present time duration}) * (\text{strain at present quarter} - \text{strain at previous time duration})$

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, it 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.

In this particular study, he has used two sets of “normalization factors”: (1) 120 mg/dL; (2)

(specific meal number / total meal number) * 120 mg/dL.

Note: For a more detailed description, please refer to the “consolidated method” section which is given at the beginning of the special issue.

3. RESULTS

Figure 1 shows his data table.

PPG Study	US PPG	US Home	US-Café	Airlines		US Home	US-Café	Airlines
No. of Meal	3639	3290	183	84	Norm %	92%	5%	2%
Ag. F. PPG	109.5	108.6	119.7	126.5	Correlation	99%	38%	46%
Ag. S. PPG	121.6	119.6	141.2	143.9				
Avg. Carbs	12.4	11.8	19.4	22.7				
Avg. Steps	4206	4221	3756	1805				

Time	US PPG	US Home	US-Café	Airlines	US Home	US-Café	Airlines
0-min	115	119	128	134	0.99	1.07	1.11
15-min	122	120	132	136	0.93	1.03	1.14
30-min	126	124	139	143	0.86	1.15	1.19
45-min	128	127	145	147	0.80	1.21	1.21
60-min	128	126	148	150	0.87	1.23	1.25
75-min	126	123	147	150	0.85	1.23	1.25
90-min	123	121	146	150	0.81	1.22	1.25
105-min	117	115	141	146	0.80	1.18	1.22
120-min	117	114	141	146	0.80	1.18	1.22
135-min	117	115	141	141	0.80	1.18	1.18
150-min	116	114	141	141	0.80	1.18	1.18
165-min	119	117	139	138	0.80	1.16	1.15
Average	122	120	141	144	0.83	1.18	1.20

Figure 1: Data table.

Figure 2 displays the TD analysis results.

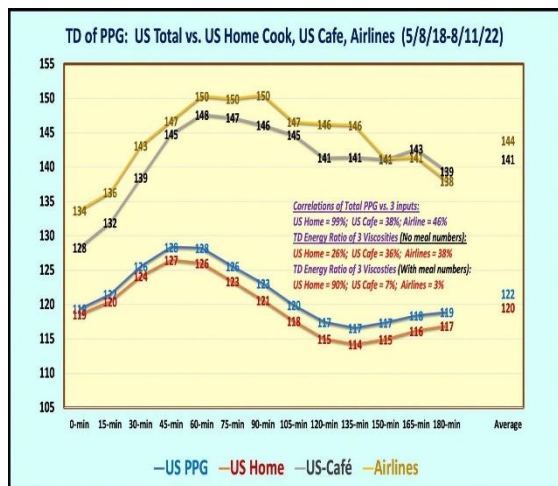


Figure 2: TD analysis results.

Figure 3 depicts the SD-VGT analysis results.

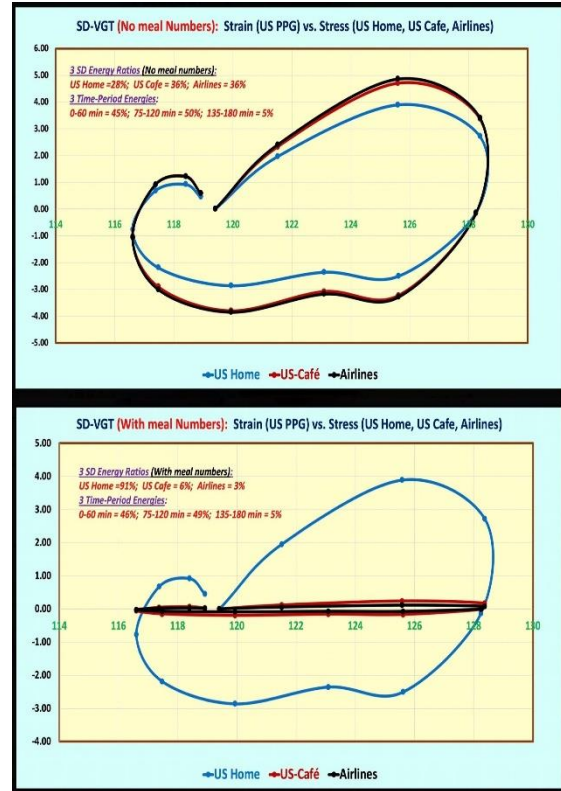


Figure 3: SD-VGT analysis results.

Figure 4 reflects the FD-FFT analysis results.



Figure 4: FD-FFT analysis results.

Figure 5 illustrates the energy comparison of using three research tools with both no meal numbers and with meal numbers.

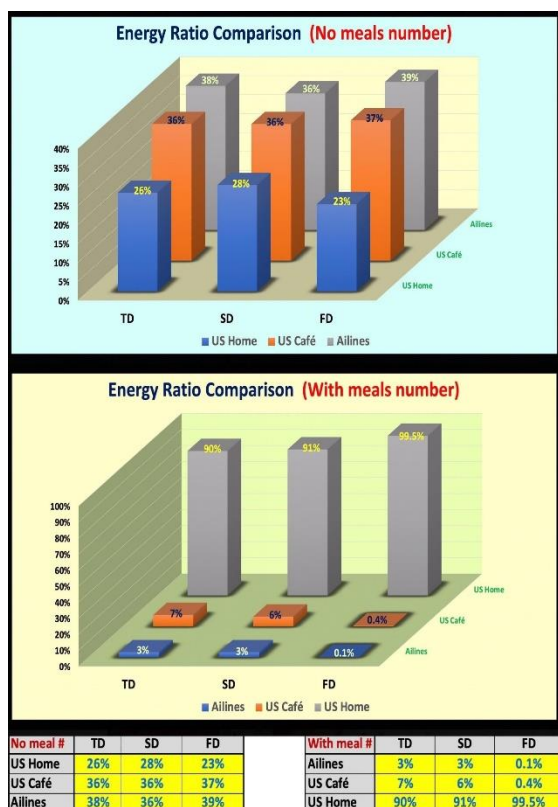


Figure 5: Energy ratio comparison for both excluding and including meal numbers into normalization factors.

4. CONCLUSION

In summary, there are 6 key findings from this special sensitivity study of normalization factors in biomedical energy analysis:

(1) From the TD diagram, the average PPG values are 122 mg/dL for US total meals, 120 mg/dL for US home-cooked meals, 141 mg/dL for US cafe meals, and 144 mg/dL for airline meals. The US home-cooked meals have better food quality control (carbs/sugar < 12 grams) and sufficient post-meal walking steps of 4,221. The US cafe meals have an average of 19 grams of carbs/sugar and also sufficient walking steps of 3,756 (restaurants focus on attracting their customers via tasty food, not healthy food). The airline-prepared meals are the worst kind because they are unhealthy (average 23 grams of carbs/sugar) and passengers cannot exercise in the airplane.

(2) From the TD diagram, the three correlation coefficients are: Total vs. Home = 99% (since home occupies 92% of total); Total vs. Cafe = 38% (low); and Total vs. Airline = 46%. Both US cafe and airline PPG characteristics are quite different from the US total meals and US home-cooked meals.

(3) TD squared-amplitude energy analysis results of both “no meal numbers” and “with meal numbers” are: For the “no meal numbers in normalization factors” case: The TD squared amplitude energy ratios are: US Home = 26%; US Cafe = 36%; and Airlines = 38%. The hyperglycemic characteristics of both US cafe meals and Airline meals influence the US total meals PPG the most. However, for the “with meal numbers in normalization factors” case: The TD squared amplitude energy ratios are: US Home = 90%; US Cafe = 7%; and Airlines = 3%. The US home-cooked meals impact the total US meals PPG the most due to its high meal numbers of 92% of US total meals.

(4) From the SD-VGT analysis results, there are two energy ratios from “no meal numbers” and “with meal numbers” which are: For the “no meal numbers in normalization factors” case: The SD-VGT energy ratios are: US Home = 28%; US Cafe = 36%; and Airlines = 36%. The hyperglycemic characteristics of both Airline and US cafes influence the US total meals PPG the most. But, for the “with meal numbers in normalization factors” case: The SD-VGT energy ratios are: US Home = 91%; US Cafe = 6%; and Airlines = 3%. The US home-cooked meals impact the total US meals PPG the most due to its 92% high meal numbers of US total meals.

(5) From the SD-VGT analysis results, he also analyzes the energy’s time-zone process from “generation through dissipation to left-over states”. Again, there are two energy ratios from “no meal numbers” and “with meal numbers” which are: For the “no meal numbers in normalization factors” case: The SD-VGT energy ratios are: 0-60 minutes = 45%; 75-120 minutes = 50%; and 135-180 minutes = 5%. But, for the “with meal numbers in normalization factors” case: The SD-VGT energy ratios are: 0-60 minutes = 46%; 75-120 minutes = 49%; and 135-180 minutes = 5%. It is interesting to find out that, regardless of the inclusion or exclusion of meal numbers inside the normalization factors, these two time-zone energy ratios are very similar to each other. In other words, generated energy via food consumption during the first hour contributes ~45%-46%, dissipated energy via exercise during the second hour contributes ~49%-50%, and left-over energy within the third hour is 5%,

regardless of inclusion or exclusion of meal numbers in the normalization factors.

(6) From the FD-FFT analysis results, there are two energy ratios from “no meal numbers” and “with meal numbers” which are: For the “no meal numbers in normalization factors” case: The FD-FFT energy ratios are: US Home = 23%; US Cafe = 37%; and Airlines = 39%. However, for “with meal numbers in normalization factors” case: The FD-FFT energy ratios are: US Home = 99.5%; US Cafe = 0.4%; and Airlines = 0.1%.

In summary, excluding the meal numbers into the normalization factors, each meal type’s biophysical characteristics of hyperglycemia would dominate the energy contribution to US total meals PPG. However, once including the meal numbers into the normalization factors, the meal type with the highest meal number would dominate the energy contribution to US total

meals PPG. This sensitivity study of the normalization process has offered a deeper understanding of biophysical behaviors of various biomedical variables, i.e. biomarkers. This article has further proven the usefulness of math-physical medicine research methodology in medical research.

5. 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.eclairemd.com.

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Viscoelastic and Viscoplastic Glucose Theory Application in Medicine

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