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Daily Glucoses Versus FPG, PPG And Glucose In Other Time Periods Using Both Time-Domain Waves And Frequency-Domain Waves Via Fourier Transform And Applying Viscoelastic Energy Model Of GH-Method: Math-Physical Medicine (No. 1019, Viscoelastic Medicine Theory #417)

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Category: Dementia

Abstract

Since May 1, 2018, the author has been employing a continuous glucose monitoring device (CGM) attached to his upper arm, enabling the collection of glucose values 96 times each day. Over a span of 2,080 days from 5/1/2018 to 1/10/2024, he has amassed a total of 199,680 glucose data points. Within each day, those 96 data points from the 24-hour time period are further categorized as follows: fasting glucose in the early morning (FPG) for 7 hours, postprandial plasma glucose (PPG) for 9 hours including three-hour ranges for each meal, and the combined between-meal and pre-bed glucoses for the remaining 8 hours of each day (Others).

At first, he utilized the conventional time-domain analysis to assess the influence of these three glucose category inputs on the resulting strain of daily estimated average glucose (eAG). Following this, a Fourier Transform operation was carried out to transform the three input glucose data sets into the frequency domain, enabling the examination of the power spectral density (PSD) for each glucose category. Lastly, the author employed the spatial-domain viscoplastic medicine theory (SD-VMT) energy model to conduct two distinct energy studies: one using the time-domain (TD) data and the other utilizing the frequency-domain data (FD).

In summary, the glucose energy analysis using the spatial-domain viscoplastic medicine theory (SD-VMT) indicates that there are notable differences between the results of energy ratios obtained from time-domain (TD) inputs and frequency-domain (FD) inputs.

In the TD diagram, the averaged glucose wave's amplitudes are ranked below:

- ***PPG: 121 mg/dL***
- ***Others: 118 mg/dL***
- ***FPG: 101 mg/dL***

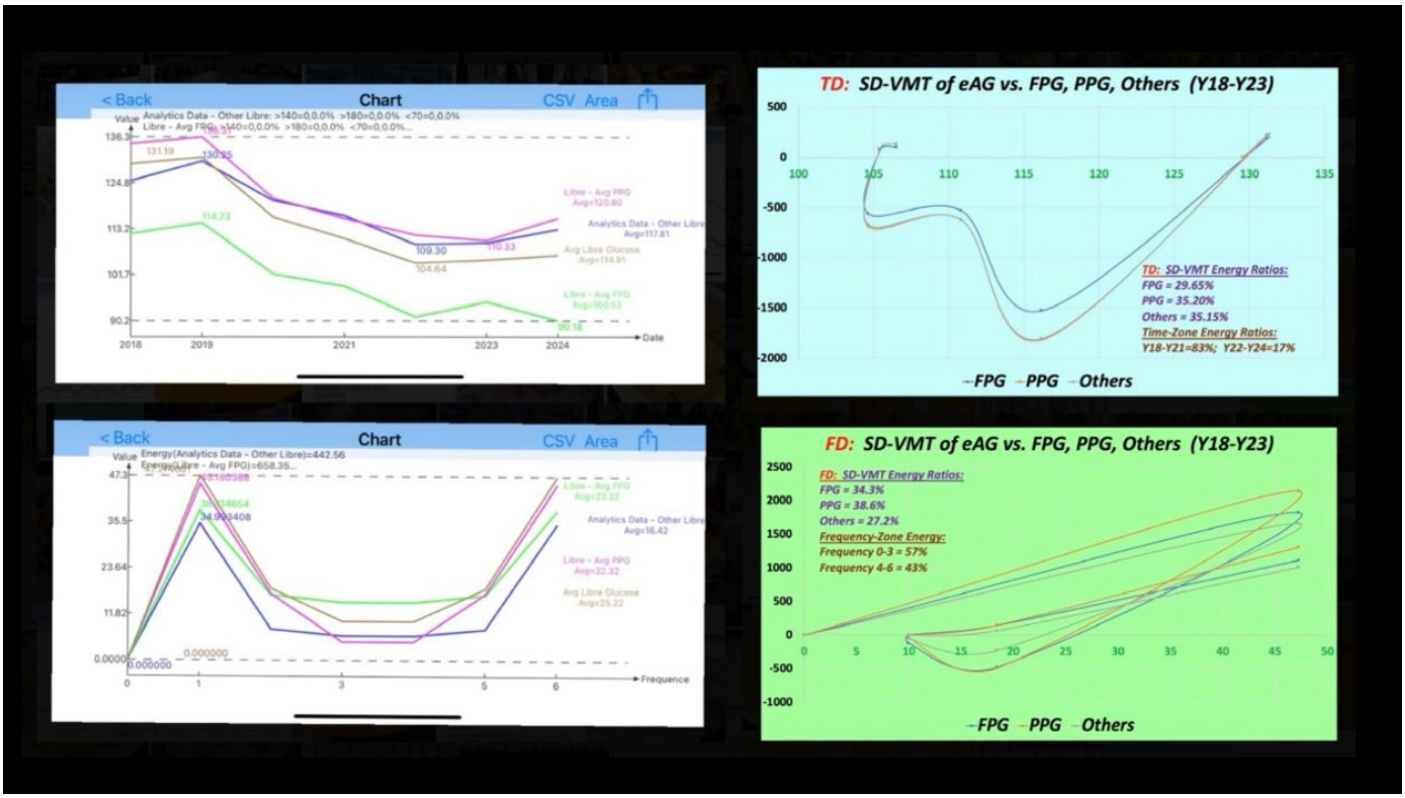
Consequently, their TD energy ranking orders are:
- ***PPG: 35.20%***
- ***Others: 35.15%***
- ***FPG: 29.65%***

However, in the FD diagram, the power spectral densities for PPG (38%) and FPG (36%) are considerably higher than for Others (26%). As a result, their FD energy ranking orders are:
- ***FPG: 38.6%***
- ***PPG: 34.3%***
- ***Others: 27.2%***

Key Messages

Based on the author's personal data, the higher energy ratios in the frequency-domain analysis suggest a significant impact on his overall diabetes control from both the hypoglycemic effects of FPG (39%) and the

hyperglycemic effects of PPG (34%).



1. Introduction

Since May 1, 2018, the author has been employing a continuous glucose monitoring device (CGM) attached to his upper arm, enabling the collection of glucose values 96 times each day. Over a span of 2,080 days from 5/1/2018 to 1/10/2024, he has amassed a total of 199,680 glucose data points. Within each day, those 96 data points from the 24-hour time period are further categorized as follows: fasting glucose in the early morning (FPG) for 7 hours, postprandial plasma glucose (PPG) for 9 hours including three-hour ranges for each meal, and the combined between-meal and pre-bed glucoses for the remaining 8 hours of each day (Others).

At first, he utilized the conventional time-domain analysis to assess the influence of these three glucose category inputs on the resulting strain of daily estimated average glucose (eAG). Following this, a Fourier Transform operation was carried out to transform the three input glucose data sets into the frequency domain, enabling the examination of the power spectral density (PSD) for each glucose category. Lastly, the author employed the spatial-domain viscoplastic medicine theory (SD-VMT) energy model to conduct two distinct energy studies: one using the time-domain (TD) data and the other utilizing the frequency-domain data (FD).

1.1 Biomedical and Engineering information

The following sections contain excerpts and concise information drawn from multiple medical articles, which have been meticulously reviewed by the author of this paper. The author has adopted this approach as an 2.alternative to including a conventional reference list at the end of this document, with the intention of optimizing his valuable research time. It is essential to clarify that these sections do not constitute part of the author's original contribution but have been included to aid the author in his future reviews and offer valuable insights to other readers with an interest in these subjects.

2. Pathophysiological Explanations and Statistical Evidence of Differences among Daily Glucose, FPG, PPG, and Glucose beside Fasting and Post-Meal (Others)

Diabetes is a metabolic disorder that is characterized by elevated levels of glucose in the blood. The understanding of different glucose levels, such as daily glucose, fasting plasma glucose (FPG), postprandial glucose (PPG), and glucose levels aside from fasting and post-meal, is crucial in managing and understanding the pathophysiology of diabetes. Here are the pathophysiological explanations and statistical evidence of the differences among these glucose levels:

2.1 Daily Glucose: Daily glucose levels represent the range of blood sugar levels throughout the day, including before and after meals as well as during periods of fasting. In individuals without diabetes, daily glucose levels typically remain within a narrow range. However, in people with diabetes, there can be significant fluctuations in daily glucose levels due to impaired insulin production or function.

2.1.1 Pathophysiological Explanation: In diabetes, the pathophysiological mechanism involves either insufficient insulin production (Type 1 diabetes) or impaired insulin action

(Type 2 diabetes). This leads to an inability of cells to take up glucose effectively, resulting in elevated blood glucose levels throughout the day.

2.1.2 Statistical Evidence: Continuous glucose monitoring (CGM) studies provide statistical evidence of daily glucose fluctuations in individuals with diabetes. CGM data show patterns of blood sugar levels throughout the day, including postprandial spikes and periods of hypoglycemia or hyperglycemia.

2.2 Fasting Plasma Glucose (FPG): FPG refers to the glucose level measured after an overnight fast, typically before breakfast in the morning. FPG is an important clinical indicator used in the diagnosis and management of diabetes, as it reflects baseline glucose control.

2.2.1 Pathophysiological Explanation: In diabetes, elevated FPG levels are primarily attributed to increased hepatic glucose production due to reduced insulin action and increased glucagon secretion. This results in higher fasting blood glucose levels.

2.2.2 Statistical Evidence: Large-scale epidemiological studies, such as the National Health and Nutrition Examination Survey (NHANES) and the Diabetes Control and Complications Trial (DCCT), have provided statistical evidence linking elevated FPG levels with an increased risk of diabetes-related complications.

2.2.3 Postprandial Glucose (PPG): PPG refers to the glucose level measured after meals, typically 1-2 hours after eating. Postprandial spikes in glucose levels are common in individuals with impaired glucose regulation.

2.2.4 Pathophysiological Explanation: After a meal, the digestion and absorption of carbohydrates lead to an increase in blood glucose. In diabetes, impaired insulin secretion or action can result in inadequate postprandial glucose control, leading to elevated PPG levels.

2.2.5 Statistical Evidence: Studies have demonstrated that high PPG levels are associated with an increased risk of cardiovascular disease and microvascular complications in diabetes patients. These studies include clinical trials such as the ACCORD trial and the DECODE study.

2.4 Glucose Levels beside Fasting and Post-Meal (Others): This category encompasses glucose levels measured at various times throughout the day, including random glucose measurements. These levels can provide insight into glucose variability and control at different times.

2.4.1 Pathophysiological Explanation: Fluctuations in glucose levels besides fasting and post-meal are influenced by factors such as physical activity, stress, medication dosing, and hormonal fluctuations. In diabetes, inadequate glucose control can lead to erratic glucose levels throughout the day.

2.4.2 Statistical Evidence: Ambulatory glucose monitoring and studies using continuous glucose monitoring (CGM) devices have provided statistical evidence of glucose variability and its impact on diabetes management and complications.

In summary, understanding these different glucose levels and their pathophysiological implications is crucial for effectively managing diabetes and reducing the risk of associated complications. Statistical evidence from clinical trials, epidemiological studies, and continuous monitoring technologies has helped elucidate the impact of daily glucose fluctuations on diabetes-related outcomes.

3. Differences between a Time-Domain Curve and a Frequency-Domain Curve after Fourier Transform Operation

After performing a Fourier transform operation on a time-domain signal, the resulting curve can be represented in either the time domain or the frequency domain. Here are the key differences between a time-domain curve and a frequency-domain curve after a Fourier transform operation:

3.1 Time-Domain Curve or Wave

3.1.1 Representation: In the time domain, the signal is plotted as a function of time, with the x-axis representing time and the y-axis representing the amplitude of the signal at each time point.

3.1.2 Information: The time-domain curve provides information about how the signal varies with time, showing the behavior and characteristics of the signal over time, such as amplitude changes and time-dependent patterns.

3.1.3 Peaks and Valleys: In the time-domain curve, peaks and valleys correspond to the specific points in time where the signal reaches its maximum and minimum amplitudes, respectively.

3.1.4 Example: For example, an audio waveform representing a musical note over time is typically plotted in the time domain, showing how the air pressure changes over time to create the sound.

3.2 Frequency-Domain Curve or Wave

3.2.1 Representation: In the frequency domain, the signal is plotted as a function of frequency, with the x-axis representing frequency and ***the y-axis representing the magnitude or phase of each frequency component present in the signal.***

3.2.2 Information: The frequency-domain curve provides information about the frequency content of the signal, revealing the specific frequencies and their respective amplitudes that make up the original time-domain signal.

3.2.3 Peaks and Peaks: In the frequency-domain curve, peaks correspond to the specific frequencies present in the signal, and their heights represent the magnitude or strength of each frequency component.

3.2.4 Example: For example, the frequency-domain representation of a musical note would reveal the fundamental frequency (corresponding to the pitch of the note) and any harmonics or overtones present in the sound.

The key difference between a time-domain curve and a

frequency-domain curve after a Fourier transform operation lies in the representations and information provided. The time domain represents the signal as a function of time, while the frequency domain reveals the underlying frequency components and their magnitudes within the signal. Each domain offers unique insights into the characteristics and properties of the original signal, making them valuable for different types of analysis and processing.

The y-axis of the frequency-domain curve typically represents the magnitude or power spectral density of the frequency component at each frequency. It shows how much of that particular frequency is present in the signal and provides information about the strength of the signal at each frequency.

The energy level associated with a specific frequency component can be calculated by integrating the power spectral density over the frequency range of interest. This calculation can provide information about the total energy carried by the signal at that particular frequency.

Therefore, the amplitude on the y-axis in the frequency domain does not directly represent the energy level of the signal at a specific frequency, but it does indicate the strength or magnitude of the frequency component within the signal.

The power spectral density (PSD) is a measure used in frequency domain analysis to describe the distribution of power or energy of a signal across different frequencies. It provides information about the strength of the signal at different frequencies and is a key tool in signal processing, communications, and other fields.

Mathematically, the power spectral density is typically calculated using the Fourier transform, which enables the signal to be represented in terms of its frequency components. The PSD quantifies how the power of the signal is distributed across these frequency components.

The PSD can be used to analyze the frequency content of a signal, identify dominant frequency components, compare the power levels at different frequencies, and assess the overall energy of a signal within specific frequency ranges. ***In technical terms, the PSD at a particular frequency provides the average power per unit frequency at that frequency. The power spectral density is a fundamental concept in frequency domain analysis, providing valuable information about the power or energy distribution of a signal across different frequencies.***

The power spectral density (PSD) of a signal can be calculated using the Fourier transform. The formula for the PSD depends on whether you are working with a discrete-time signal (such as a sampled signal from a sensor or a digital recording) or a continuous-time signal.

For a ***discrete-time signal x[n],*** where n represents the sample index, the PSD S_xx(f) can be calculated as follows:

$$S_{xx}(f) = |X(f)|^2$$

Where:
- X(f) is the discrete-time Fourier transform (DTFT) of the signal x[n] evaluated at frequency f.
- |X(f)|^2 represents the magnitude squared of the DTFT.

The ***discrete-time Fourier transform X(f) for a discrete-time signal x[n]*** is given by the formula:

$$X(f) = \Sigma [x[n] * e^{(-j2\pi fn/N)}]$$

Where:
- Σ denotes the summation over all n
- x[n] is the value of the signal at sample index n
- j is the imaginary unit
- f is the frequency (in cycles per sample)
- N is the total number of samples

For ***a continuous-time signal x(t)***, the PSD S_xx(f) can be calculated as follows:

$$S_{xx}(f) = \lim_{T\to\infty} (1/T)|X(f)|^2$$

Where:
- X(f) is the Fourier transform of the signal x(t) evaluated at frequency f
- |X(f)|^2 represents the magnitude squared of the Fourier transform
- T is the total duration of the signal

In practical applications, ***the PSD is often estimated using methods such as the periodogram, Welch method, or multitaper method, especially for discrete-time signals. These methods involve dividing the signal into segments, computing the Fourier transform for each segment, and averaging the resulting power spectra to estimate the PSD.***

It is important to note that the PSD provides valuable information about the frequency content and power distribution of a signal, making it a crucial tool in signal processing, communications, and various engineering and scientific fields.

4. MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from his published 760+ 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.

5. The Author'S Diabetes History

The author was a severe T2D patient since 1995. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C at 10%).

During that year, his triglycerides reached 1161 (high risk for CVD and stroke) and his albumin-creatinine ratio (ACR) at 116 (high risk for chronic kidney disease). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding the need for kidney dialysis treatment and the future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with an emphasis on diabetes and food nutrition. He spent the entire year of 2014 to develop a metabolism index (MI) mathematical model. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and HbA1C (A1C). Through using his developed mathematical metabolism index (MI) model and the other four glucose prediction tools, by the end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger-piercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes-related medications since 12/8/2015.

In 2017, he achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period, including both 2018 and 2019, he traveled to ~50 international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control caused by stress, dining out frequently, post-meal exercise disruption, and jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was somewhat affected during the two-year traveling period of 2018-2019.

He started his COVID-19 self-quarantined life on 1/19/2020. By 10/16/2022, his weight was further reduced to ~164 lbs. (BMI 24.22) and his A1C was at 6.0% without any medication intervention or insulin injection. In fact, with the special COVID-19 quarantine lifestyle since early 2020, not only has he written and published ~500 new research articles in various medical and engineering journals, but he has also achieved his best health conditions for the past 27 years. These achievements have resulted from his non-traveling, low-stress, and regular daily life routines. Of course, his in-depth knowledge of chronic diseases, sufficient practical lifestyle management experiences, and his own developed high-tech tools have also contributed to his excellent health improvements.

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. Furthermore, he extracted the 5-minute intervals from every 15-minute interval for a total of 96 glucose data each day stored in his computer software.

Through the author's medical research work over 40,000 hours and read over 4,000 published medical papers online in the past 13 years, he discovered and became convinced that good life habits of not smoking, moderate or no alcohol intake, avoiding illicit drugs; along with eating the right food with well-balanced nutrition, persistent exercise, having a sufficient and good quality of sleep, reducing all kinds of unnecessary stress, maintaining a regular daily life routine contribute to the risk reduction of having many diseases, including CVD, stroke, kidney problems, micro blood vessels issues, peripheral nervous system problems, and even cancers and dementia. In addition, a long-term healthy lifestyle can even "repair" some damaged internal organs, with different required time-length depending on the particular organ's cell lifespan. For example, he has "self-repaired" about 35% of his damaged pancreatic beta cells during the past 10 years.

6. Energy Theory

The human body and organs have around 37 trillion live cells which are composed of different organic cells that require energy infusion from glucose carried by red blood cells; and energy consumption from labor-work or exercise. When the residual energy (resulting from the plastic glucose scenario) is stored inside our bodies, it will cause different degrees of damage or influence to many of our internal organs.

According to physics, energies associated with the glucose waves are proportional to the square of the glucose amplitude. The residual energies from elevated glucoses are circulating inside the body via blood vessels which then impact all of the internal organs to cause different degrees of damage or influence, e.g. diabetic complications. Elevated glucose (hyperglycemia) causes damage to the structural integrity of blood vessels. When it combines with both hypertension (rupture of arteries) and hyperlipidemia (blockage of arteries), CVD or Stroke happens. Similarly, many other deadly diseases could result from these excessive energies which would finally shorten our lifespan. For an example, the combination of hyperglycemia and hypertension would cause micro-blood vessel's leakage in kidney systems which is one of the major cause of CKD.

The author then applied Fast Fourier Transform (FFT) operations to convert the input wave from a time domain into a frequency domain. The y-axis amplitude values in the frequency domain indicate the proportional energy levels associated with each different frequency component of input occurrence. ***Both output symptom value (i.e. strain amplitude in the time domain) and output symptom fluctuation rate (i.e. the strain rate and strain frequency) are influencing the energy level (i.e. the Y-amplitude in the frequency domain).***

Currently, many people live a sedentary lifestyle and lack sufficient exercise to burn off the energy influx which causes them to become overweight or obese. Being overweight and having obesity leads to a variety of chronic diseases, particularly diabetes. In addition, many types of processed food add unnecessary ingredients and harmful chemicals that are toxic to the bodies, which lead to the development of many other deadly diseases, such as cancers. For example, ~85% of worldwide diabetes patients are overweight, and ~75% of patients with cardiac illnesses or surgeries have diabetes conditions.

In engineering analysis, when the load is applied to the structure, it bends or twists, i.e. deform; however, when the load is removed, it will either be restored to its original shape (i.e, elastic case) or remain in a deformed shape (i.e. plastic case). In a biomedical system, the glucose level will increase after eating carbohydrates or sugar from food; therefore, the carbohydrates and sugar function as the energy supply. After having labor work or exercise, the glucose level will decrease. As a result, the exercise burns off the energy, which is similar to load removal in the engineering case. In the biomedical case, both processes of energy influx and energy dissipation take some time which is not as simple and quick as the structural load removal in the engineering case. Therefore, the age difference and 3 input behaviors are "dynamic" in nature, i.e. time-dependent. This time-dependent nature leads to a "viscoelastic or viscoplastic" situation. ***For the author's case, it is "viscoplastic" since most of his biomarkers are continuously improved during the past 13-year time window***.

Time-dependent output strain and stress of (viscous input*output rate)

Hooke's law of linear elasticity is expressed as:

Strain (ε: epsilon)
= Stress (σ: sigma) / Young's modulus (E)

For biomedical glucose application, his developed linear elastic glucose theory (LEGT) is expressed as:

PPG (strain) = carbs/sugar (stress) * GH.p-Modulus (a positive number) + post-meal walking k-steps * GH.w-Modulus (a negative number)

Where GH.p-Modulus is reciprocal of Young's modulus E.

However, in viscoelasticity or viscoplasticity theory, the stress is expressed as:

Stress
= viscosity factor (η: eta) * strain rate (dε/dt)

Where strain is expressed as Greek epsilon or ε.

In this article, in order to construct an "ellipse-like" diagram in a stress-strain space domain (e.g. "hysteresis loop") covering both the positive side and negative side of space, he has modified the definition of strain as follows:

Strain
= (body weight at certain specific time instant)

He also calculates his strain rate using the following formula:

Strain rate
= (body weight at next time instant) - (body weight at present time instant)

The risk probability % of developing into CVD, CKD, Cancer is calculated based on his developed metabolism index model (MI) in 2014. His MI value is calculated using inputs of 4 chronic conditions, i.e. weight, glucose, blood pressure, and lipids; and 6 lifestyle details, i.e. diet, drinking water, exercise, sleep, stress, and daily routines. These 10 metabolism categories further contain ~500 elements with millions of input data collected and processed since 2010. For individual deadly disease risk probability %, his mathematical model contains certain specific weighting factors for simulating certain risk percentages associated with different deadly diseases, such as metabolic disorder-induced CVD, stroke, kidney failure, cancers, dementia; artery damage in heart and brain, micro-vessel damage in kidney, and immunity-related infectious diseases, such as COVID death.

Some of explored deadly diseases and longevity characteristics using the ***viscoplastic medicine theory (VMT)*** include stress relaxation, creep, hysteresis loop, and material stiffness, damping effect ***based on time-dependent stress and strain*** which are different from his previous research findings using ***linear elastic glucose theory (LEGT) and nonlinear plastic glucose theory (NPGT)***.

7. Results

TD - eAG					/ 1	/ 1	/ 1	S. Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3	Time Zone	Pred.	Pred.	Pred.
1/11/23	eAG	FPG	PPG	Others	FPG	PPG	Others	eAG	eAG	FPG	PPG	Others	FPG	PPG	Others	FPG	PPG	Others		Step 1	Step 2	eAG
2018	130	112	135	125	112	135	125	0.00	130	0	0	0	0	0	0	0	0	0	Y18-Y21	125	1	130
2019	131	115	136	130	115	136	130	1.63	131	187	222	212	94	111	106	152	181	173	53033	128	1	129
2020	116	102	121	120	102	121	120	-14.99	116	-1527	-1812	-1804	-670	-795	-796	10046	11918	11931	83%	115	1	116
2021	111	99	116	117	99	116	117	-5.38	111	-532	-623	-627	-1030	-1218	-1216	5539	6552	6541		111	1	112
2022	105	91	112	109	91	112	109	-6.18	105	-563	-690	-675	-548	-657	-651	3384	4059	4026	Y22-Y23	105	1	106
2023	105	95	110	110	95	110	110	0.76	105	72	84	83	-246	-303	-296	-187	-230	-225	11176	106	1	107
2024	107	90	116	113	90	116	113	1.15	107	104	133	130	88	109	107	101	125	123	17%	107	1	108
Avg	115	101	121	118	101	121	118	-3.29	115	-323	-384	-383	-330	-393	-392	19036	22604	22569		114	1	115
Correl.	100%	98%	99%	97%										SD-E:	64209	29.65%	35.20%	35.15%	Accuracy =	99%	R =	100%

FD - eAG					/ 1	/ 1	/ 1	S. Rate	Strain	Strs 1	Strs 2	Strs 3	Hgt 1	Hgt 2	Hgt 3	Area 1	Area 2	Area 3	Freq Zone	Pred.	Pred.	Pred.
1/11/23	eAG	FPG	PPG	Others	FPG	PPG	Others	eAG	eAG	FPG	PPG	Others	FPG	PPG	Others	FPG	PPG	Others		Step 1	Step 2	eAG
0	0	0	0	0	0	0	0	0.00	0	0	0	0	0	0	0	0	0	0	Freq 0-3	0	0	0
1	47	38	45	35	38	45	35	47.27	47	1816	2136	1654	908	1068	827	42926	50487	39103	74963	40	2	48
2	18	17	17	8	17	17	8	-28.86	18	-482	-492	-230	667	822	712	-19258	-23731	-20556	57%	14	1	17
3	10	15	5	6	15	5	6	-8.43	10	-125	-40	-53	-303	-266	-142	2558	2240	1193		9	0	10
4	10	15	5	6	15	5	6	0.00	10	0	0	0	-63	-20	-27	0	0	0	Freq 4-6	9	0	10
5	18	17	17	8	17	17	8	8.43	18	141	144	67	70	72	34	593	605	283	55949	14	1	17
6	47	38	45	35	38	45	35	28.86	47	1109	1304	1010	625	724	539	18032	20891	15545	43%	40	2	48
Avg	22	20	19	14	20	19	14	6.75	22	351	436	350	272	343	278	44852	50492	35568		18	1	22
Correl.	100%	98%	99%	98%	38%	36%	26%							SD-E:	130913	34.3%	38.6%	27.2%	Accuracy =	100%	R =	100%

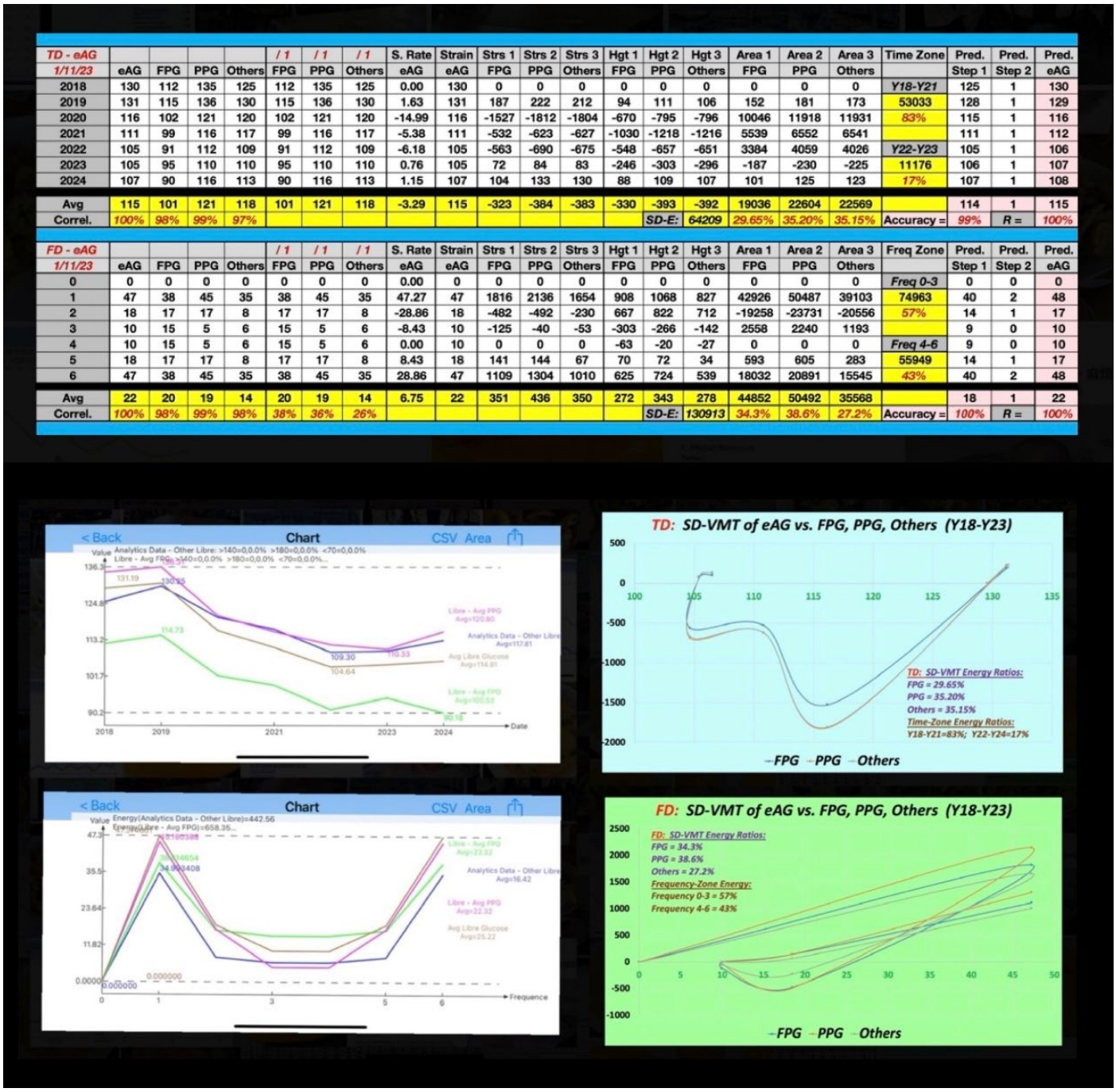


Figure 1: Data table, inputs and SD-VMT energy output diagram

8. Conclusions

In summary, the glucose energy analysis using the spatial-domain viscoplastic medicine theory (SD-VMT) indicates that there are notable differences between the results of energy ratios obtained from time-domain (TD) inputs and frequency-domain (FD) inputs.

In the TD diagram, the averaged glucose wave's amplitudes are ranked below:

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Key Messages

Based on the author's personal data, the higher energy ratios in the frequency-domain analysis suggest a significant impact on his overall diabetes control from both the hypoglycemic effects of FPG (39%) and the hyperglycemic effects of PPG (34%).

References

For editing purposes, 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.

Readers may use this article as long as the work is properly cited, and their use is educational and not for profit, and the author's original work is not altered.

For reading more of the author's published VGT or FD analysis results on medical applications, please locate them through platforms for scientific research publications, such as ResearchGate, Google Scholar, etc.