The GH-Method

Nonlinear Plastic Glucose Theory (NPGT #5): Applying Three Models, NPGT, Perturbation Theory, and Statistics Regression Analysis to Predict and Investigate Postprandial Plasma Glucose Data, Waveforms, and Behavior Using 23 Hyperglycemic Meals Above 180 mg/dL Based on GH-Method: Math-Physical Medicine (No. 575)

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Note: Readers who want to get a quick overview can read the abstract, results, and graphs only, and ignore other sections.

Abstract

The author applies linear elastic glucose theory (LEGT), nonlinear plastic glucose theory (NPGT), energy theory, wave theory, signal processing techniques, perturbation theory and statistics regression analysis to conduct multiple series of medical research work, where he has written 100+ medical papers on studying various biomarker behaviors, especially glucose. This NPGT paper number 5 combines the perturbation theory and regression analysis models to compare the pros and cons of 3 different math-physical research methodologies. In this study, he utilized his collected 23 meals data with high glucose level i.e., "hyperglycemic" situation above 180 mg/dL, as the base of input data. In medicine, the human body with its various organs and cells are organic and go through many distinct stages over their natural lifespans, such as birth, splitting, growth, mutation, development, repair, sickness, and death. Therefore, the biomedical properties are "moving targets" which vary with the individual person, severity of diabetes, and selected time-windows of study. Even so, they still possess some hidden biophysical or biochemical phenomena in the organs and diseases which are interrelated; therefore, one of the major missions for medical research scientists is to explore and identify the hidden relationship. Using the signal processing technique, he has identified that the postprandial plasma glucose (PPG) biomarker has around 19 influential factors. Among these factors, the most prominent two are diet and exercise. However, carbs/sugar intake amount and post-meal walking k-steps are also dynamic variables, which are different from meal to meal. By combining these inherent complexity and dynamic behaviors of both human organs and lifestyle details, it is extremely difficult to predict an exact PPG behavior, level, or trend. The above paragraph has provided a rough view on the complexity of biomedical problems. Since 2015, the author has conducted various research work to identify a few reliable ways to predict PPG. His research methodology tools include physics (elasticity theory, plasticity theory, energy theory, and wave theory), quantum mechanics (perturbation theory), statistics (correlation and regression) and others. Similar to a car engine requiring both oxygen and fuel, the human body and its organs are composed of different organic cells that require energy infusion from oxygen and glucose (nutrition) carried by red blood cells along with energy consumption from labor-work or exercise. When the residual energy resulting from plastic glucose scenario i.e., high glucose level which cannot be brought back to its initial lower level, is stored inside the body, it will cause different degrees of damage to the internal organs. According to physics, energies associated with the residual glucose waves are directly proportional to the square of the residual glucose amplitude. These residual energies from elevated glucoses are then circulating inside the body via blood vessels which would impact all of our internal organs to cause varying degrees of damage. The author has also applied Fast Fourier Transform (FFT) operations to convert the glucose 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 occurrence, which is the occurrence frequency of certain glucose components. The above descriptions have provided the specific reason why the author is investigating hyperglycemic meals in this article. He has developed a data-mining capability in his software to explore, identify, and select 23 PPG data and their associated waveforms which have the

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hyperglycemic (greater than 180 mg/dL) phenomena from his database containing 4,048 meals over the past 3.7 years. These total 4,048 meals have an averaged PPG value of 111.5 mg/dL which is a result from an average carbs/sugar intake amount of 13.9 grams and post-meal walking of 4,282 steps. However, there are 4,025 meals which are ~99.5% of the total 4,048 meals that fall below 180 mg/dL level. They possess an "elastic" glucose behavior. Its synthesized PPG waveform starts from 123 mg/dL at 0-minute, where his PPG value increased due to the consumption of 11.2 grams of carbs&sugar for energy input (low energy input or low stress) and reaches a PPG peak level of 133 mg/dL at 60-minutes, before starting to decline due to walking exercise, which burns off the energy to finally return to its ending-PPG level of 122 mg/dL at 180-minutes. This end-glucose value returning to its initial-glucose position, after burning off energy influx, is called "elastic". On the contrary, another different scenario of the glucose behavior can be explained using 23 meals with "plastic glucose" behaviors (~0.5% of total meals). A synthesized PPG waveform, by combining all of the 23 PPG curves together, has the following different biophysical plastic behavior pattern. Its synthesized PPG waveform starts from 142 mg/dL at 0-minute, where his PPG value increases due to the consumption of 90 grams of carbs&sugar for energy input (high energy input or high stress) and reaches to the first PPG peak level of 189 mg/dL at 60-minutes and then continuously climbs but with a lower slope (44% of earlier elastic phase) due to the combined effect of his excessive carbs&sugar consumption and normal routine of post-meal walking exercise (3.5 k-steps), until it reaches to another peak PPG level of 207 mg/dL at 120-minutes. At this instant, the sole effect from his walking exercise finally kicks in to burn off the energy intake until it decreases to the end-glucose level of 191 mg/dL at 180-minutes. This end-glucose value of 191 mg/dL is still 49 mg/dL higher than its initial-glucose position of 142 mg/dL. This type of "permanent deformation" or "residual glucose" value of 49 mg/dL is called "plastic" or "elasto-plastic". The above explanation is based on physics concepts such as elasticity theory, plasticity theory, wave theory, and energy theory. At first, he used the NPGT model to develop the predicted PPG with two different input levels of carbs/sugar intake amounts of 90 grams and 60 grams, respectively. Second, he uses a perturbation theory model for the 60 grams carbs/sugar case to develop another perturbed PPG dataset of lower values. Third, he finally uses a statistics regression analysis model to compare: real PPG with 90 grams versus NPGT PPG with 90 grams and perturbed PPG with 60 grams versus NPGT PPG with 60 grams. The objectives of conducting this particular study are three-fold: (1) Identify prediction accuracy and PPG waveform similarity (via correlation) comparison among four sets of hyperglycemic cases of real PPG (1), NPGT PPG (2), perturbed PPG (1), and regression PPG (2); (2) Explore the analysis model's applicability to identify the most suitable method and application situation. Or, if possible, to identify a combination of multiple analysis methods for a hyperglycemic problem; (3) Compare pros and cons of using each of the three analysis models from viewpoints of hyperglycemic control. His research work utilized a selected case of 23 hyperglycemic meals which led him to the following three conclusive findings: (1) His developed NPGT model not only contains the most components of the physical meaning and interpretation of the biomedical problem at hand, but it is also simplified and the easiest model to be used among the 3 models to obtain a quick, simple, yet highly accurate (96%-100%) PPG prediction for hyperglycemia. (2) His applied perturbation theory model offers a good result for the NPGT model in terms of both prediction accuracy (97%) and waveform similarity (100%). This perturbation model is a combined model which starts with a known biophysical dataset with a diminishing "perturbation parameter from biophysics", which is then followed with a series of numerical operations. (3) His statistics regression analysis model for this particular case has shown high enough prediction accuracy (96%-100%) and extremely high waveform or curve similarity (100%). However, this statistics regression model is a pure numerical operation tool which does not possess any physical knowledge of the biomedical problem. Therefore, its applicability varies from one problem such as the selected dataset to another problem. However, the author has also identified one way to improve its applicability which is to obtain the NPGT PPG dataset first and then conduct the statistics regression analysis for either real versus NPGT or perturbation versus NPGT. This combination approach has greatly improved the waveform similarity i.e., correlation, to make them reach 100% (similar to the real and perturbed PPG waveforms). Here is the final summary of his findings: Plasticity theory contains the physical meaning of a biomedical problem which is the simplest one to use and it achieves a very high prediction accuracy along with waveform similarity. The perturbation model sits in the middle which uses an existing biophysical sample with a biophysical or biochemical meaning from both outputs (glucose) and inputs (diet or exercise) with the rest of its process as a numerical operation. The regression model is a pure statistical numerical operation which has no linkage to any physics meanings or interpretations for the biomedical problem; therefore, its usefulness or accuracy is connected with the specific data sampling, data size, and time window selection. However, if we use elasticity or plasticity first to construct an estimated glucose curve (with high accuracy) and then run a regression analysis between the real curve and the plastic predicted curve, this results in an extremely high correlation of 100% (i.e., identical waveforms) and prediction accuracy.

Keywords: Linear elastic glucose theory; Nonlinear plastic glucose theory; Glucose; Diabetes

Abbreviations: LEGT: linear elastic glucose theory; NPGT: nonlinear plastic glucose theory; T2D: type 2 diabetes; FPG: fasting plasma glucose; PPG: postprandial plasma glucose; CGM: continuous glucose monitoring; MPM: math-physical medicine

1. INTRODUCTION

The author applies linear elastic glucose theory (LEGT), nonlinear plastic glucose theory (NPGT), energy theory, wave theory, signal processing techniques, perturbation theory and statistics regression analysis to conduct multiple series of medical research work, where he has written 100+ medical papers on studying various biomarker behaviors, especially glucose. This NPGT paper number 5 combines the perturbation theory and regression analysis models to compare the pros and cons of 3 different math-physical research methodologies. In this study, he utilized his collected 23 meals data with high glucose level i.e., "hyperglycemic" situation above 180 mg/dL, as the base of input data.

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Since 2015, the author has conducted various research work to identify a few reliable ways to predict PPG. His research methodology tools include physics (elasticity theory, plasticity theory, energy theory, and wave theory), quantum mechanics (perturbation theory), statistics (correlation and regression) and others.

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The above descriptions have provided the specific reason why the author is investigating hyperglycemic meals in this article. He has developed a data-mining capability in his software to explore, identify, and select 23 PPG data and their associated waveforms which have the hyperglycemic (greater than 180 mg/dL) phenomena from his database containing 4,048 meals over the past 3.7 years. These total 4,048 meals have an averaged PPG value of 111.5 mg/dL which is a result from an average carbs/sugar intake amount of 13.9 grams and post-meal walking of 4,282 steps.

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The above explanation is based on physics concepts such as elasticity theory, plasticity theory, wave theory, and energy theory. At first, he used the NPGT model to develop the predicted PPG with two different input levels of carbs/sugar intake amounts of 90 grams and 60 grams, respectively. Second, he uses a perturbation theory model for the 60 grams carbs/sugar case to develop another perturbed PPG dataset of lower values. Third, he finally uses a statistics regression analysis model to compare: real PPG with 90 grams versus NPGT PPG with 90 grams and perturbed PPG with 60 grams versus NPGT PPG with 60 grams.

2. METHODS

2.1 MPM background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from the published 400+ medical papers.

The first paper, No. 386, describes his MPM methodology in a general conceptual format. The second paper, No. 387, 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, depicts a general flow diagram containing ~10 key MPM research methods and different tools.

All of the listed papers in the References section are from his written and published medical research papers.

2.2 The author's case of diabetes

The author has been a severe T2D patient since 1996. He weighed 220 lb. (100 kg, BMI 32.5) at that time. By 2010, he still weighed 198 lb. (BMI 29.2) with an average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached 1161 and albumin-creatinine ratio (ACR) at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and his future high risk of dying from his severe diabetic complications. Other than cerebrovascular disease (stroke), he has suffered most of known diabetic complications, including both macrovascular and microvascular complications.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition in order to save his own life. During 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, postprandial plasma glucose (PPG), fasting plasma glucose (FPG), and A1C. As a result, from using his developed mathematical metabolism index (MI) model in 2014 and the four 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 since 12/8/2015.

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 metabolism 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 heavier traveling period.

During 2020-2021 with a COVID-19 quarantined lifestyle, not only has he published ~500 medical papers in 100+ journals, but he has also reached his best health conditions for the past 28 years. By Y2021, his weight was further reduced to 165 lbs. (BMI 24.4) along with a 5.8% A1C value on 10/22/2021, without having any medication interventions or insulin injections. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his knowledge of chronic diseases, practical lifestyle management experiences, and developed various high-tech tools contribute to his excellent health status since 1/19/2020, the beginning date of his COVID-19 quarantined life.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checked his glucose measurements every 5 minutes for a total of ~288 times each day. He has maintained the same measurement pattern to present day. In his research work, he uses his CGM sensor glucose at a time-interval of 15 minutes (96 data per day). By the way, the difference of average sensor glucoses between 5-minute intervals and 15-minute intervals is only 0.4% (average glucose of 114.81 mg/dL for 5-minutes and average glucose of 114.35 mg/dL for 15-minutes with a correlation of 93% between these two sensor glucose curves) during the period from 2/19/20 to 8/13/21.

Therefore, over the past 12 years, he could study and analyze the 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 medical research work is based on the aims of achieving both "high precision" with "quantitative proof" in the medical findings.

The following timetable provides a rough sketch of the emphasis of 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 LEGT and perturbation theory from quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia.

Again, to date, he has collected more than two million data regarding his medical conditions and lifestyle details. In addition, he has written 572 medical papers and published 500+ papers in 100+ various medical journals. Moreover, he has also given ~120 presentations at ~65 international medical conferences. He has continuously dedicated his time and efforts on his medical research work and shared his findings and learnings with other patients worldwide.

2.3 Elasticity and plasticity

The following paragraphs are excerpts from Wikipedia:

“Elasticity (physics)

Physical property when materials or objects return to original shape after deformation.

In physics and materials science, elasticity is the ability of a body to resist a distorting influence and to return to its original size and shape when that influence or force is removed. Solid objects will deform when adequate loads are applied to them; if the material is elastic, the object will return to its initial shape and size after removal. This is in contrast to plasticity, in which the object fails to do so and instead remains in its deformed state.

The physical reasons for elastic behavior can be quite different for different materials. In metals, the atomic lattice changes size and shape when forces are applied (energy is added to the system). When forces are removed, the lattice goes back to the original lower energy state. For rubbers and other polymers, elasticity is caused by the stretching of polymer chains when forces are applied.

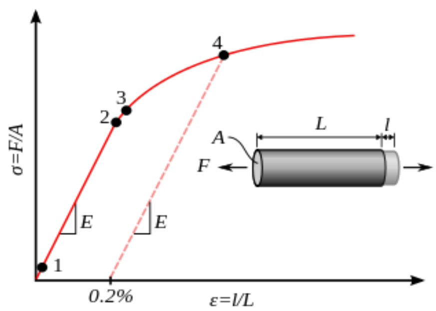
Hooke's law states that the force required to deform elastic objects should be directly proportional to the distance of deformation, regardless of how large that distance becomes. This is known as perfect elasticity, in which a given object will return to its original shape no matter how strongly it is deformed. This is an ideal concept only; most materials which possess elasticity in practice remain purely elastic only up to very small deformations, after which plastic (permanent) deformation occurs.

In engineering, the elasticity of a material is quantified by the elastic modulus such as the Young's modulus, bulk modulus or shear modulus which measure the amount of stress needed to achieve a unit of strain; a higher modulus indicates that the material is harder to deform. The material's elastic limit or yield strength is the maximum stress that can arise before the onset of plastic deformation.

Plasticity (physics)

Deformation of a solid material undergoing non-reversible changes of shape in response to applied forces.

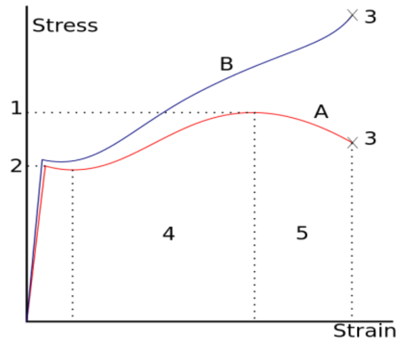
In physics and materials science, plasticity, also known as plastic deformation, is the ability of a solid material to undergo permanent deformation, a non-reversible change of shape in response to applied forces. For example, a solid piece of metal being bent or pounded into a new shape displays plasticity as permanent changes occur within the material itself. In engineering, the transition from elastic behavior to plastic behavior is known as yielding.



Stress–strain curve showing typical yield behavior for nonferrous alloys.

1. True elastic limit
2. Proportionality limit

3. Elastic limit
4. Offset yield strength



A stress–strain curve typical of structural steel.

- 1: Ultimate strength
- 2: Yield strength (yield point)
- 3: Rupture
- 4: Strain hardening region
- 5: Necking region
- A: Apparent stress (F/A0)
- B: Actual stress (F/A)

Plastic deformation is observed in most materials, particularly metals, soils, rocks, concrete, and foams. However, the physical mechanisms that cause plastic deformation can vary widely. At a crystalline scale, plasticity in metals is usually a consequence of dislocations. Such defects are relatively rare in most crystalline materials, but are numerous in some and part of their crystal structure; in such cases, plastic crystallinity can result. In brittle materials such as rock, concrete and bone, plasticity is caused predominantly by slip at microcracks. In cellular materials such as liquid foams or biological tissues, plasticity is mainly a consequence of bubble or cell rearrangements, notably T1 processes.

For many ductile metals, tensile loading applied to a sample will cause it to behave in an elastic manner. Each increment of load is accompanied by a proportional increment in extension. When the load is removed, the piece returns to its original size. However, once the load exceeds a threshold – the yield strength – the extension increases more rapidly than in the elastic region; now when the load is removed, some degree of extension will remain.

Elastic deformation, however, is an approximation and its quality depends on the time frame considered and loading speed. If, as indicated in the graph opposite, the deformation includes elastic deformation, it is also often referred to as "elasto-plastic deformation" or "elastic-plastic deformation".

Perfect plasticity is a property of materials to undergo irreversible deformation without any increase in stresses or loads. Plastic materials that have been hardened by prior deformation, such as cold forming, may need increasingly higher stresses to deform further. Generally, plastic deformation is also dependent on the deformation speed, i.e. higher stresses usually have to be applied to increase the rate of deformation. Such materials are said to deform visco-plastically."

2.4 Perturbation theory

In this study, the author will not provide a detailed explanation of the perturbation theory in this section of Method because it is available in modern physics or quantum mechanics textbooks. However, he inserts the following paragraphs from Wikipedia as excerpt:

"Perturbation theory:

In math and applied mathematics, methods for finding an approximate solution to a problem.

This article is about perturbation theory as a general mathematical method. For perturbation theory applied specifically to quantum mechanics, see Perturbation theory (quantum mechanics).

In mathematics and applied mathematics, perturbation theory comprises methods for finding an approximate solution to a problem, by starting from the exact solution of a related, simpler problem. A critical feature of the technique is a middle step that breaks the problem into "solvable" and "perturbative" parts. In perturbation theory, the solution is expressed as a power series in a small parameter ε. The first term is the known solution to the solvable problem. Successive terms in the series at higher powers of ε usually become smaller. An approximate 'perturbation solution' is obtained by truncating the series, usually by keeping only the first two terms, the solution to the known problem and the 'first order' perturbation correction.

Perturbation theory is used in a wide range of fields, and reaches its most sophisticated and advanced forms in quantum field theory. Perturbation theory (quantum mechanics) describes the use of this method in quantum mechanics. The field in general remains actively and heavily researched across multiple disciplines.

Perturbation theory develops an expression for the desired solution in terms of a formal power series known as a perturbation series in some "small" parameter, that quantifies the deviation from the exactly solvable problem. The leading term in this power series is the solution of the exactly solvable problem, while further terms describe the deviation in the solution, due to the deviation from the initial problem. Formally, we have for the approximation to the full solution A, a series in the small parameter (here called ε), like the following:

A=A0+ε1A1+ε2A2+⋯

In this example, A0 would be the known solution to the exactly solvable initial problem and A1, A2, ... represent the first-order, second-order and higher-order terms, which may be found iteratively by a mechanistic procedure. For small ε these higher-order terms in the series generally (but not always) become successively smaller. An approximate "perturbative solution" is obtained by truncating the series, often by keeping only the first two terms, expressing the final solution as a sum of the initial (exact) solution and the "first-order" perturbative correction

A≈A0+εA1(ε→0)

Some authors use big O notation to indicate the order of the error in the approximate solution:

A=A0+εA1+O(ε2)."

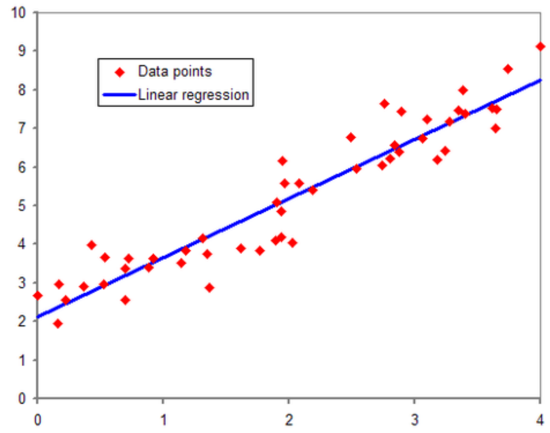
2.5 Regression analysis models

In this study, the author will not provide a detailed explanation of the statistical regression analysis in the Methods section because it is available in many statistics textbooks. However, he inserts the following paragraphs from Wikipedia as an excerpt:

"Regression analysis:

Set of statistical processes for estimating the relationships among variables.

In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome' or 'response' variable) and one or more independent variables (often called 'predictors', 'covariates', 'explanatory variables' or 'features'). The most common form of regression analysis is linear regression, in which one finds the line (or a more complex linear combination) that most closely fits the data according to a specific mathematical criterion. For example, the method of ordinary least squares computes the unique line (or hyperplane) that minimizes the sum of squared differences between the true data and that line (or hyperplane).



Regression line for 50 random points in a Gaussian distribution around the line y=1.5x+2 (not shown).

Regression analysis is primarily used for two conceptually distinct purposes. First, regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Second, in some situations regression analysis can be used to infer causal relationships between the independent and dependent variables. Importantly, regressions by themselves only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset. To use regressions for prediction or to infer causal relationships, respectively, a researcher must carefully justify why existing relationships have predictive power for a new context or why a relationship between two variables has a causal interpretation. The latter is especially important when researchers hope to estimate causal relationships using observational data."

It should be noted that in regression analysis, the correlation coefficient R should be > 0.5 or 50% to indicate a strong inter-connectivity and the p-value should be < 0.05 or 5% to be considered as statistically significant.

3. RESULTS

Figure 1 shows the master data table which includes 1 real measured data, 2 NPGT data, 1 perturbed data, and 2 regression data.

Figure 2 depicts the resulting 6 hyperglycemic PPG waveforms. Please note that other than two NPGT PPG curves with 3-segments, all of the other 4 waveforms have exceedingly high curve similarity (100% of correlations). All 5 PPG values have extremely high prediction accuracy (greater than 96%) in comparison against the real PPG.

Figure 3 demonstrates the supporting data and graphs for regression analysis.

1/6/22						
23 hypoglycemia meals	90g & 3.532k	NPGT vs. Real (90g)	60g & 4k	NPGT vs. Pert (60g)	Real vs. NPGT (90g)	NPGT vs. Pert (60g)
5/8/18-12/31/21	Real (90g)	NPGT (90g)	NPGT (60g)	Pert-1st: (60g)	Reg. Real/NPGT (90g)	Reg. Pert/NPGT (60g)
0-min	142	142	142	142	143	143
15-min	153	152	149	147	152	149
30-min	163	162	157	153	161	156
45-min	177	172	164	160	172	164
60-min	187	182	172	164	180	169
75-min	192	186	175	167	184	172
90-min	202	190	179	172	192	178
105-min	204	195	182	173	193	179
120-min	207	199	185	174	196	181
135-min	203	195	181	172	193	179
150-min	207	191	176	174	196	181
165-min	203	186	172	172	193	179
180-min	191	184	168	167	183	172
Average	187	180	169	164	180	169
Accuracy	100%	96%	100%	97%	96%	100%
Correlation	100%	99%	97%	100%	100%	100%
GH-Moduls for 23	GH.e for 79.3g	GH.p for 79.3g	GH.w for 79.3g	GH.e for 60g	GH.p for 60g	GH.w for 60g
GH-Modu;us Value	0.505	0.222	-4.434	0.505	0.222	-4.434
Carbs & Sugar	High-carbs	Selected	Low-carbs	1st order		
Selection of Carbs	90	65.0	40	0.50		

Figure 1: Data table of real data and three analysis models, NPGT, perturbation, and regression.

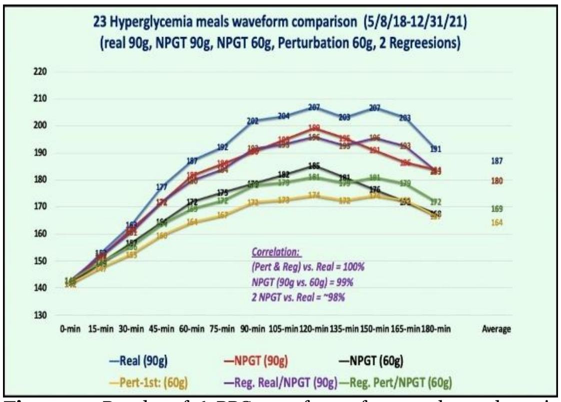


Figure 2: Results of 6 PPG waveforms from 23 hyperglycemic meals.

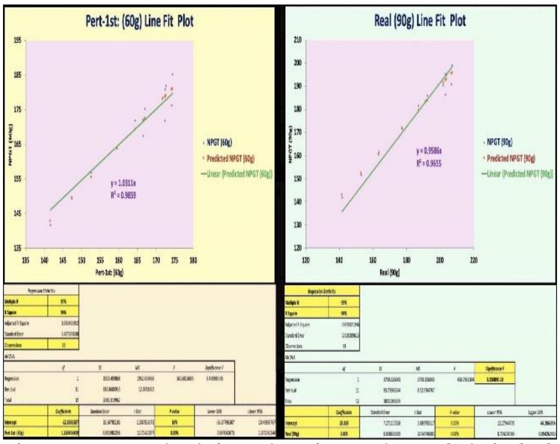


Figure 3: Supporting information of regression analysis for both 90 g and 60 g cases.

4. CONCLUSION

The objectives of conducting this particular study are three-fold:

(1) Identify prediction accuracy and PPG waveform similarity (via correlation) comparison among four sets of hyperglycemic cases of real PPG (1), NPGT PPG (2), perturbed PPG (1), and regression PPG (2);

(2) Explore the analysis model's applicability to identify the most suitable method and application situation. Or, if possible, to identify a combination of multiple analysis methods for a hyperglycemic problem;

(3) Compare pros and cons of using each of the three analysis models from viewpoints of hyperglycemic control.

His research work utilized a selected case of 23 hyperglycemic meals which led him to the following three conclusive findings:

(1) His developed NPGT model not only contains the most components of the physical

meaning and interpretation of the biomedical problem at hand, but it is also simplified and the easiest model to be used among the 3 models to obtain a quick, simple, yet highly accurate (96%-100%) PPG prediction for hyperglycemia.

(2) His applied perturbation theory model offers a good result for the NPGT model in terms of both prediction accuracy (97%) and waveform similarity (100%). This perturbation model is a combined model which starts with a known biophysical dataset with a diminishing "perturbation parameter from biophysics", which is then followed with a series of numerical operations.

(3) His statistics regression analysis model for this particular case has shown high enough prediction accuracy (96%-100%) and extremely high waveform or curve similarity (100%). However, this statistics regression model is a pure numerical operation tool which does not possess any physical knowledge of the biomedical problem. Therefore, its applicability varies from one problem such as the selected dataset to another problem. However, the author has also identified one way to improve its applicability which is to obtain the NPGT PPG dataset first and then conduct the statistics regression analysis for either real versus NPGT or perturbation versus NPGT. This combination approach has greatly improved the waveform similarity i.e., correlation, to make them reach 100% (similar to the real and perturbed PPG waveforms).

Here is the final summary of his findings:

Plasticity theory contains the physical meaning of a biomedical problem which is the simplest one to use and it achieves a very high prediction accuracy along with waveform similarity. The perturbation model sits in the middle which uses an existing biophysical sample with a biophysical or biochemical meaning from both outputs (glucose) and inputs (diet or exercise) with the rest of its process as a numerical operation. The regression model is a pure statistical numerical operation which has no linkage to any physics meanings or interpretations for the biomedical problem; therefore, its usefulness or accuracy is connected with the specific data sampling, data size, and time window selection. However, if we use elasticity or plasticity first to construct an estimated glucose curve (with high accuracy) and then run a regression analysis between the real curve and the plastic predicted curve, this results in an extremely high correlation of 100% (i.e., identical waveforms) and prediction accuracy.

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.