The GH-Method

Nonlinear Plastic Glucose Theory (NPGT #6): A Reference Table for Predicted Hyperglycemic Situations above 180 mg/dL of Postprandial Plasma Glucose Values to be Used by Type 2 Diabetes Patients on their Daily Glucose Control Efforts Based on GH-Method: Math-Physical Medicine (No. 576)

Gerald C. Hsu*

eclaireMD Foundation, USA

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 from physics; signal processing techniques from electronic and electrical engineering; perturbation theory from quantum mechanics; and regression analysis from statistics to conduct multiple medical research work, where he has written 100+ medical papers on studying the biomarker behaviors, especially glucose. This NPGT paper number 6 uses a combined model of nonlinear plastic glucose theory and statistical regression analysis to develop a simple and clear reference table of hyperglycemic situations for severe type 2 diabetes (T2D) patients. Any T2D patient user can select a carbs/sugar intake amount from the vertical y-column, e.g., 70 grams, 90 grams, or 110 grams and match it with a corresponding post-meal walking k-steps, e.g., 2.0 k-steps, 4.0 k-steps, or 6.0 k-steps, from the horizontal x-row to view one box of the x-y plane. Within this box, it contains five key predicted postprandial plasma glucose (PPG) values: 0-minute, 60-minutes, 120-minutes, 180-minutes, and average PPG over a 3-hour timespan. For other input data of carbs/sugar amount or post-meal walking k-steps, users can perform an interpretation to determine the approximate answers. Although these predicted values will not be 100% accurate due to certain built-in assumptions and some approximation techniques used at different stages of this numerical process, the predicted PPG results are still accurate enough for T2D patients to predict their daily hyperglycemic conditions when consuming high amounts of carbs/sugar. This specific tool of predicting high glucose levels can provide a warning before they consume food or meals and begin their post-meal exercises. As a starting point, the author uses his collected 23 meals PPG data with high glucoses i.e., "hyperglycemic" situations above 180 mg/dL, as the baseline of his database. He has developed a data-mining capability in his software to explore, identify, and select 23 PPG data and their associated waveforms which have hyperglycemic phenomena from his database containing 4,048 meals over the past 3.7 years. These total 4,048 meals have an average 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. This NPGT paper number 6 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 his 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

Available online: 26 July 2023

*Corresponding author: Gerald C. Hsu, eclaireMD Foundation, USA

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". This study involves three steps. At first, he retains the plastic glucose case from the synthesized 23 meals as the baseline comparison. Second, he uses the NPGT model to predict PPG values with three different input levels of carbs/sugar intake amounts of 70 grams, 90 grams, and 110 grams, respectively. Within each carbs/sugar category, he has subdivided them into three exercise levels, 2.0 k-steps, 4.0 k-steps, and 6.0 k-step. The NPGT model provides a high accuracy of predicted PPG (prediction accuracies are 98%-99%). Third, he uses statistics regression analysis model to construct a total of 9 regression predicted PPG waveforms. The regression analysis model provides an identical waveform similarity as the real case from 23 hyperglycemic meals with a correlation = 100%. 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 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 provide the specific reason why the author developed this useful hyperglycemic PPG prediction table for other T2D patients. In summary, by examining the 3 data tables and 9 PPG waveforms (3 carbs/sugar times 3 walking k-steps), the following four conclusions have outlined some important findings from this study: (1) For the NPGT prediction case of 90 grams and 4.0 k-steps versus the real case of 90 grams and 3.5 k-steps, the prediction accuracy has reached 98.9%. For the regression prediction case of 90 grams and 4.0 k-steps versus the real case of 90 grams and 3.5 k-steps, the prediction accuracy has also reached 98.9%. (2) For all NPGT prediction cases, the range of correlations, such as waveform similarities, ranges from 93% to 99%. For all regression prediction cases, the range of correlations, such as waveform similarities, are 100%, where all regression curves have identical waveform similarity as the real PPG curve. (3) It is evident that the NPGT model generates highly accurate predicted PPG values while the regression model preserves their predicted waveform shapes which are the same as the baseline real curve. (4) Due to the nature of plastic glucose behavior which is mainly caused by over-consumed carbs/sugar amounts, any normal level of exercise or activity after a meal and within the time limit of 2 hours will not burn off the energy influx completely. Therefore, as a hyperglycemic concern, it is safe to conclude that the diet control with a limited carb/sugar intake amount is far more important than exercise. Incidentally, for elastic glucose cases, post-meal exercise is a very effective way to completely burn off energy influx.

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 from physics; signal processing techniques from electronic and electrical engineering; perturbation theory from quantum mechanics; and regression analysis from statistics to conduct multiple medical research work, where he has written 100+ medical papers on studying the biomarker behaviors, especially glucose.

This NPGT paper number 6 uses a combined model of nonlinear plastic glucose theory and statistical regression analysis to develop a simple and clear reference table of hyperglycemic situations for severe type 2 diabetes (T2D) patients. Any T2D patient user can select a carbs/sugar intake amount from the vertical y-column, e.g., 70 grams, 90 grams, or 110 grams and match it with a corresponding post-meal walking k-steps, e.g., 2.0 k-steps, 4.0 k-steps, or 6.0 k-steps, from the horizontal x-row to view one box of the x-y plane. Within this box, it contains five key predicted postprandial plasma glucose (PPG) values: 0-minute, 60-minutes, 120-minutes, 180-minutes, and average PPG over a 3-hour timespan. For other input data of carbs/sugar amount or post-meal walking k-steps, users can perform an interpretation to determine the approximate answers.

Although these predicted values will not be 100% accurate due to certain built-in assumptions and some approximation techniques used at different stages of this numerical process, the predicted PPG results are still accurate enough for T2D patients to predict their daily hyperglycemic conditions when consuming high amounts of carbs/sugar. This specific tool of predicting high glucose levels can provide a warning before they consume food or meals and begin their post-meal exercises.

As a starting point, the author uses his collected 23 meals PPG data with high glucoses i.e., "hyperglycemic" situations above 180 mg/dL, as the baseline of his database. He has developed a data-mining capability in his software to explore, identify, and select 23 PPG data and their associated waveforms which have hyperglycemic phenomena from his database containing 4,048 meals over the past 3.7 years. These total 4,048 meals have an average 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. This NPGT paper number 6 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 his 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".

This study involves three steps. At first, he retains the plastic glucose case from the synthesized 23 meals as the baseline comparison. Second, he uses the NPGT model to predict PPG values with three different input levels of carbs/sugar intake amounts of 70 grams, 90 grams, and 110 grams, respectively. Within each carbs/sugar category, he has subdivided them into three exercise levels, 2.0 k-steps, 4.0 k-steps, and 6.0 k-step. The NPGT model provides a high accuracy of predicted PPG (prediction accuracies are 98%-99%). Third, he uses statistics regression analysis model to construct a total of 9 regression predicted PPG waveforms. The regression analysis model provides an identical waveform similarity as the real case from 23 hyperglycemic meals with a correlation = 100%.

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 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 provide the specific reason why the author developed this useful hyperglycemic PPG prediction table for other T2D patients.

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 to 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 macro-vascular and micro-vascular 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 dinning 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 checks 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 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 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.

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+ paper 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.

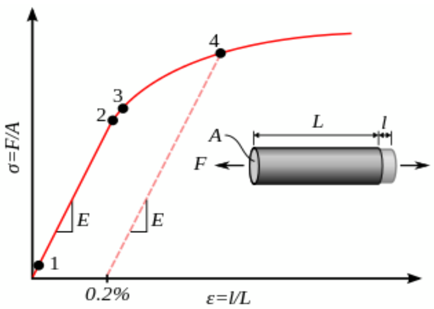
Hooke's law states that the force required to deform elastic objects should be directly proportional to the distance of deformation, regardless of how large that distance becomes. This is known as perfect elasticity, in which a given object will return to its original shape no matter how strongly it 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)

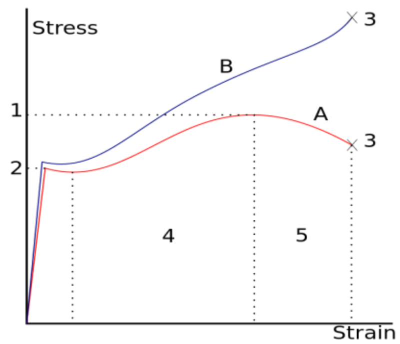
Deformation of a solid material undergoing non-reversible changes of shape in response to applied forces.

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."

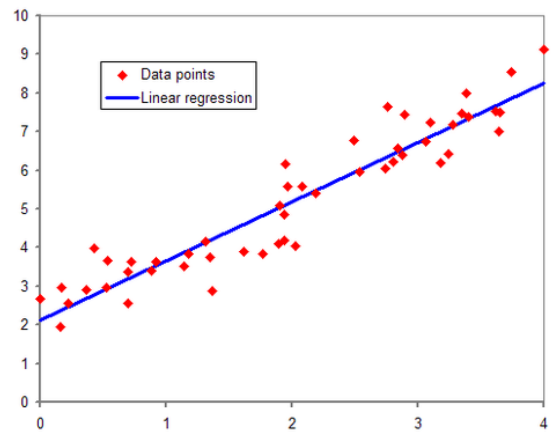
2.4 Regression analysis models

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).



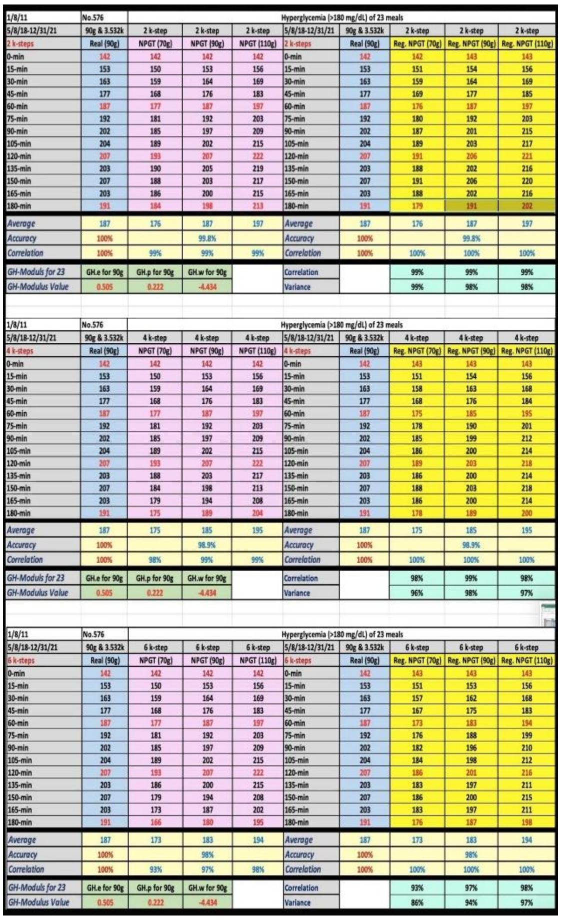
Regression line for 50 random points in a Gaussian distribution around the line y=1.5x+2 (not shown).

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 analysis results from using both NPGT model and statistics regression model of 9 cases (3 carbs/sugar amounts times 3 walking k-steps).



1/8/11	No.576	Hyperglycemia (>180 mg/dL) of 23 meals							
5/8/18-12/31/21	90g & 3.532k	2 k-step	2 k-step	2 k-step	5/8/18-12/31/21	90g & 3.532k	2 k-step	2 k-step	2 k-step
2 k-steps	Real (90g)	NPGT (70g)	NPGT (90g)	NPGT (110g)	2 k-steps	Real (90g)	Reg. NPGT (70g)	Reg. NPGT (90g)	Reg. NPGT (110g)
0-min	142	142	142	142	0-min	142	142	143	143
15-min	153	150	153	156	15-min	153	151	154	156
30-min	163	159	164	169	30-min	163	159	164	169
45-min	177	168	176	183	45-min	177	169	177	185
60-min	187	177	187	197	60-min	187	176	187	197
75-min	192	181	192	203	75-min	192	180	192	203
90-min	202	185	197	209	90-min	202	187	201	215
105-min	204	189	202	215	105-min	204	189	203	217
120-min	207	193	207	222	120-min	207	191	206	221
135-min	203	190	205	219	135-min	203	188	202	216
150-min	207	188	203	217	150-min	207	191	206	220
165-min	203	186	200	215	165-min	203	188	202	216
180-min	191	184	198	213	180-min	191	179	191	202
Average	187	176	187	197	Average	187	176	187	197
Accuracy	100%		99.8%		Accuracy	100%		99.8%	
Correlation	100%	99%	99%	99%	Correlation	100%	100%	100%	100%
GH-Moduls for 23	GH.e for 90g	GH.p for 90g	GH.w for 90g		Correlation		99%	99%	99%
GH-Modulus Value	0.505	0.222	-4.434		Variance		99%	98%	98%

1/8/11	No.576	Hyperglycemia (>180 mg/dL) of 23 meals							
5/8/18-12/31/21	90g & 3.532k	4 k-step	4 k-step	4 k-step	5/8/18-12/31/21	90g & 3.532k	4 k-step	4 k-step	4 k-step
4 k-steps	Real (90g)	NPGT (70g)	NPGT (90g)	NPGT (110g)	4 k-steps	Real (90g)	Reg. NPGT (70g)	Reg. NPGT (90g)	Reg. NPGT (110g)
0-min	142	142	142	142	0-min	142	143	143	143
15-min	153	150	153	156	15-min	153	151	154	156
30-min	163	159	164	169	30-min	163	158	163	168
45-min	177	168	176	183	45-min	177	168	176	184
60-min	187	177	187	197	60-min	187	175	185	195
75-min	192	181	192	203	75-min	192	178	190	201
90-min	202	185	197	209	90-min	202	185	199	212
105-min	204	189	202	215	105-min	204	186	200	214
120-min	207	193	207	222	120-min	207	189	203	218
135-min	203	188	203	217	135-min	203	186	200	214
150-min	207	184	198	213	150-min	207	188	203	218
165-min	203	179	194	208	165-min	203	186	200	214
180-min	191	175	189	204	180-min	191	178	189	200
Average	187	175	185	195	Average	187	175	185	195
Accuracy	100%		98.9%		Accuracy	100%		98.9%	
Correlation	100%	98%	99%	99%	Correlation	100%	100%	100%	100%
GH-Moduls for 23	GH.e for 90g	GH.p for 90g	GH.w for 90g		Correlation		98%	99%	98%
GH-Modulus Value	0.505	0.222	-4.434		Variance		96%	98%	97%

1/8/11	No.576	Hyperglycemia (>180 mg/dL) of 23 meals							
5/8/18-12/31/21	90g & 3.532k	6 k-step	6 k-step	6 k-step	5/8/18-12/31/21	90g & 3.532k	6 k-step	6 k-step	6 k-step
6 k-steps	Real (90g)	NPGT (70g)	NPGT (90g)	NPGT (110g)	6 k-steps	Real (90g)	Reg. NPGT (70g)	Reg. NPGT (90g)	Reg. NPGT (110g)
0-min	142	142	142	142	0-min	142	143	143	143
15-min	153	150	153	156	15-min	153	151	153	156
30-min	163	159	164	169	30-min	163	157	162	168
45-min	177	168	176	183	45-min	177	167	175	183
60-min	187	177	187	197	60-min	187	173	183	194
75-min	192	181	192	203	75-min	192	176	188	199
90-min	202	185	197	209	90-min	202	182	196	210
105-min	204	189	202	215	105-min	204	184	198	212
120-min	207	193	207	222	120-min	207	186	201	216
135-min	203	186	200	215	135-min	203	183	197	211
150-min	207	179	194	208	150-min	207	186	200	215
165-min	203	173	187	202	165-min	203	183	197	211
180-min	191	166	180	195	180-min	191	176	187	198
Average	187	173	183	194	Average	187	173	183	194
Accuracy	100%		98%		Accuracy	100%		98%	
Correlation	100%	93%	97%	98%	Correlation	100%	100%	100%	100%
GH-Moduls for 23	GH.e for 90g	GH.p for 90g	GH.w for 90g		Correlation		93%	97%	98%
GH-Modulus Value	0.505	0.222	-4.434		Variance		86%	94%	97%

Figure 1: Hyperglycemia analysis results using both NPGT model and regression model.

Figure 2 shows 3 NPGT PPG waveforms for different level of walking k-steps. Each diagram includes the real PPG curve and 3 NPGT curves associated with different carbs/sugar amount.

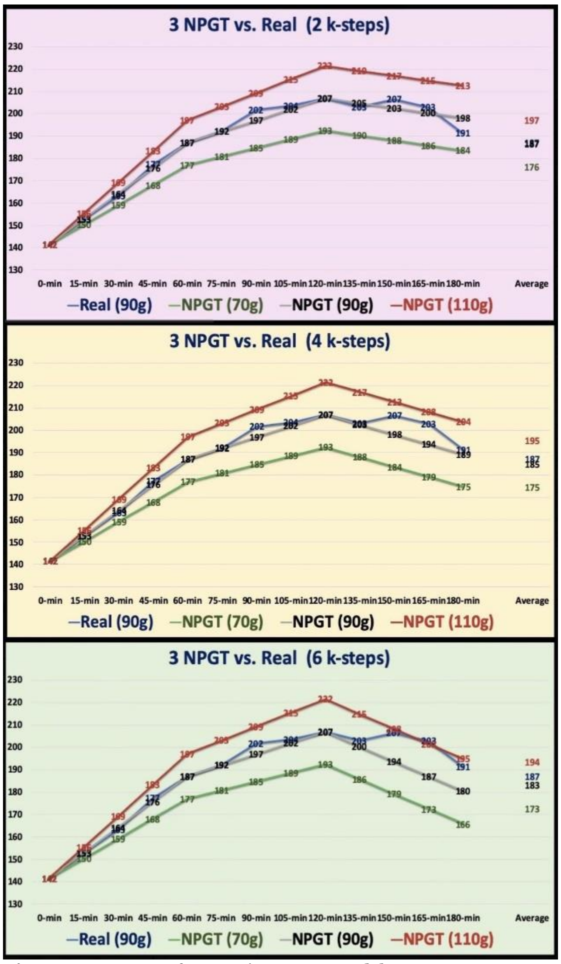


Figure 2: PPG waveforms using NPGT model.

Figure 3 shows 3 Regression PPG waveforms for different level of walking k-steps. Each diagram includes the real PPG curve and 3 NPGT curves associated with different carbs/sugar amount. Please note that they have "identical" waveform shapes resulted from the selected variables of the regression analysis model.

Figure 4 shows the hyperglycemia PPG reference table. For severe T2D patients, they can use the table tool as a "early warning" provider for controlling their hyperglycemia situations.

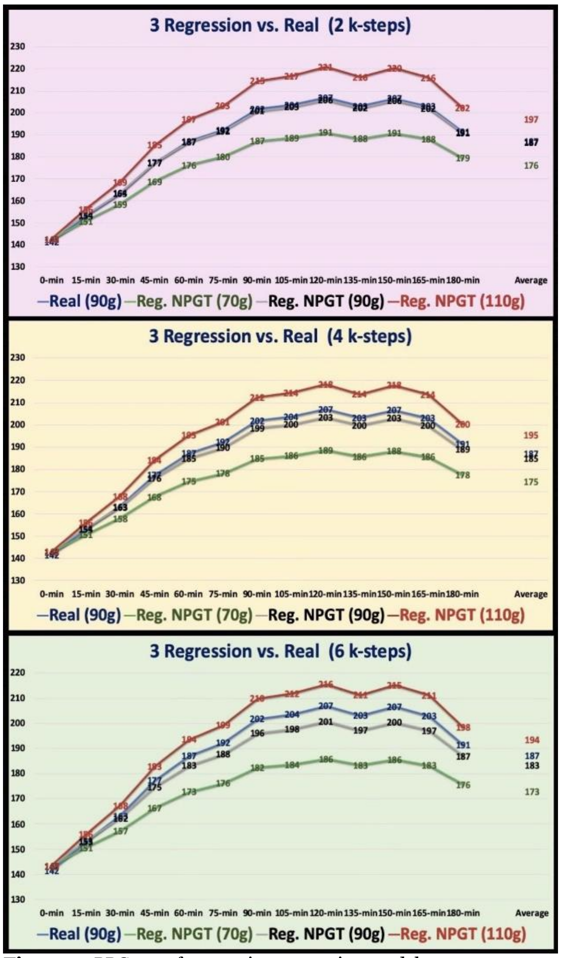


Figure 3: PPG waveforms using regression model.

Using NPGT to get PPG first, and then using Regression for NPGT vs. Real to get final Predicted PPG						
Hyperglycemia PPG	70g		90g		110g	
2.0 k-steps	0-min	142	0-min	143	0-min	143
	60-min	176	60-min	187	60-min	197
	120-min	191	120-min	206	120-min	221
	180-min	179	180-min	191	180-min	202
	Average	176	Average	187	Average	197
Hyperglycemia PPG	70g		90g		110g	
4.0 k-steps	0-min	143	0-min	143	0-min	143
	60-min	175	60-min	185	60-min	195
	120-min	189	120-min	203	120-min	218
	180-min	178	180-min	189	180-min	200
	Average	175	Average	185	Average	195
Hyperglycemia PPG	70g		90g		110g	
6.0 k-steps	0-min	143	0-min	143	0-min	143
	60-min	173	60-min	183	60-min	194
	120-min	186	120-min	201	120-min	216
	180-min	176	180-min	187	180-min	198
	Average	173	Average	183	Average	194

Figure 4: Reference table tool for T2D patients to control their hyperglycemia situations.

4. CONCLUSION

In summary, by examining the 3 data tables and 9 PPG waveforms (3 carbs/sugar times 3 walking k-steps), the following four conclusions have outlined some important findings from this study:

(1) For the NPGT prediction case of 90 grams and 4.0 k-steps versus the real case of 90 grams and 3.5 k-steps, the prediction accuracy has reached 98.9%. For the

regression prediction case of 90 grams and 4.0 k-steps versus the real case of 90 grams and 3.5 k-steps, the prediction accuracy has also reached 98.9%.

(2) For all NPGT prediction cases, the range of correlations, such as waveform similarities, ranges from 93% to 99%. For all regression prediction cases, the range of correlations, such as waveform similarities, are 100%, where all regression curves have identical waveform similarity as the real PPG curve.

(3) It is evident that the NPGT model generates highly accurate predicted PPG values while the regression model preserves their predicted waveform shapes which are the same as the baseline real curve.

(4) Due to the nature of plastic glucose behavior which is mainly caused by over-consumed carbs/sugar amounts, any normal level of exercise or activity after a meal and within the time limit of 2 hours will not burn off the energy influx completely. Therefore, as a hyperglycemic concern, it is safe to conclude that the diet control with a limited carb/sugar intake amount is far more important than exercise. Incidentally, for elastic glucose cases, post-meal exercise is a very effective way to completely burn off energy influx.

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.