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Research Article

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Using Topology Concept of Mathematics and Finite Element Method of Engineering to Develop a Mathematical Model of Metabolism in medicine in order to Control Various Chronic Diseases and their Complications via Overall Health Conditions Improvement Based on GH-Method: Math-Physical Medicine (No. 453)

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Abstract

The author spent 11 years with more than 30,000 hours to self-study and research chronic diseases and lifestyle details in order to control his severe type 2 diabetes (T2D) and various diabetic complications.

After self-studying endocrinology and food nutrition for 4 years, from 2010 to 2013, he applied the learned medicine and food knowledge combined with his background of four academic disciplines and practical experiences on mathematics, physics, engineering, and computer science (big data analytics and artificial intelligence) to develop a mathematical model of metabolism during the entire year of 2014. He continued with his development effort of several prediction tools for weight, fasting plasma glucose (FPG), postprandial plasma glucose (PPG), daily glucose, and HbA1C in 2015-2016. Starting from 2017, he started to write papers based on his findings from his research and then published them in various journals.

This particular metabolism model includes 10 major categories: 4 medical conditions including weight (M1), glucose (M2), blood pressure (M3), lipids (M4); with 6 lifestyle details including exercise (M5), water intake (M6), sleep (M7), stress (M8), food and meal (M9), and life routines regularity (M10). These 10 categories contain approximately 500 input and output elements. For example, he spent 9 months on developing the stress category with 34 elements. The total number of data collected and processed during the past 10 years have already exceeded 2 million.

During 2015 to 2021, for a period of 6.5 years, he applied many theories and techniques from mathematics, physics, and engineering into his medical research work. This included topology, nonlinear algebra, finite element method, linear elastic theory, wave theory, energy theory, quantum mechanics, optical physics, statistics, machine learning, big data analytics, and artificial intelligence (AI). These various theories and techniques have effectively served as his research tools in order to complete many of the medical research tasks.

As a result, his collected personal data of both biomarkers and lifestyle details were utilized to illustrate the development process of building a metabolism model of medicine using topology concept of mathematics, finite element method of engineering along with other applicable theories and principles of physics (applied math) and engineering (applied physics).

This paper describes the author's selected approach of building a mathematical model of metabolism. It uses the topology concept, part of finite element engineering modeling technique, applicable theories and principles from physics and engineering, such as optical physics, energy theory, wave theory, linear elasticity, perturbation theory of quantum mechanics, and various computer science and AI tools to investigate and develop a rather complicated metabolism model in a highly quantitative manner. Optimistically and pleasantly, it has actually achieved certain high prediction accuracy in results based on a simple concept but rather general scope of "Metabolism".

Introduction

The author spent 11 years with more than 30,000 hours to self-study and research chronic diseases and lifestyle details in order to control his severe type 2 diabetes (T2D) and various diabetic complications.

After self-studying endocrinology and food nutrition for 4 years, from 2010 to 2013, he applied the learned medicine and food knowledge combined with his background of four academic disciplines and practical experiences on mathematics, physics, engineering, and computer science (big data analytics and artificial intelligence) to develop a mathematical model of metabolism during the entire year of 2014. He continued with his development effort of several prediction tools for weight, fasting plasma glucose (FPG), postprandial plasma glucose (PPG), daily glucose, and HbA1C in 2015-2016. Starting from 2017, he started to write papers based on his findings from his research and then published them in various journals.

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Methods and Results

Topology Concept

The following definitions of topology are quoted from the Oxford dictionary and Wikipedia.

From Oxford dictionary: "*The definition of Topology is the study of geometric properties and spatial relations unaffected by the continuous change of shape or size of figures*."

From Wikipedia: "*In mathematics, topology is concerned with the properties of a geometric object that are preserved under continuous deformations, such as stretching, twisting, crumpling, and bending; that is, without closing holes, opening holes, tearing, gluing, or passing through itself*."

In early 2014, the author made an observation that the human body with its various internal organs are similar to the concept of a topological subject, where their fundamental characteristics are retained under various types and degrees of deformation, as long as there is no partial rupture of organ or total break-down of health. In other words, poor lifestyle habits may twist, warp, damage, or "deform" the organs and bodies (but without cut-off, break-down, or removal, i.e., no discontinuity); however, the human body and organs will preserve their original characteristics and continue functioning as they were originally designed. Of course, the subject's performance data (biomarkers) would be altered or changed somewhat due to poor lifestyle, which is similar to the different external shapes of a topological subject. This concept of topology and non-linear geometric algebra provides one of his basic principles of his follow-on medical research tasks.

Finite Element Method

Any complicated system can be decomposed into many similar or different basic construction elements which are usually easier to be analyzed, assembled, solved and understood. After solving problems associated with certain basic elements, we can then "reassemble" all of the building elements back to the original total system in order to get an approximate, yet accurate enough, solution and achieve a better understanding of the original system, human body, or internal organs. This is the essence of "finite element method" in medicine.

The following diagram in Figure 1 depicts the governing equation of finite element metabolism model:

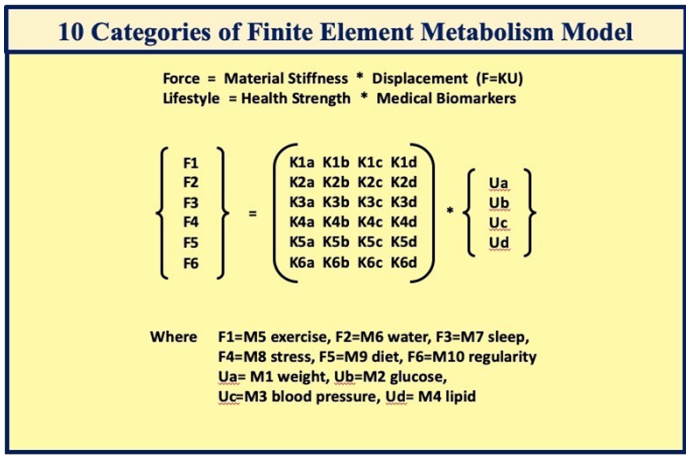

Figure 1: Equation of finite element metabolism model

The author provides a few examples to illustrate his developed finite element metabolism equation and model.

First, let us study one element (e.g., PPG) of a particular category of glucose, M2. His earlier research articles indicated that the biomarker PPG value has a linear relationship with his post-meal walking steps of lifestyle details at -5 mg/dL per each +1,000 walking steps. This is a simpler example that provides his K1b value (stiffness of glucose vs. exercise) at a linear rate of -0.005. Over here, the correlation between PPG and post-meal waking steps is a negative high value of -67%.

On the other hand, PPG is also directly related to our diet situation, particularly the carbs/sugar intake amount (grams). This relationship can be expressed through a range of stiffness values which are depending upon food type, overall health conditions,

stage of diabetes, and other environment factors. The particular stiffness values of K5b (glucose vs. carbs/sugar) are located within a wide range of +1 to +10. For the author's case, his most commonly observed stiffness value is around 2.0 which means each gram of consumed carbs or sugar would generate 2 mg/dL of his glucose after meal. The correlation between PPG and carbs/sugar intake amount is high positive value of +59%.

Interestingly, there is also a close relationship (with a suitable stiffness value and a pretty high positive correlation coefficient of +67%) existing between the sleep category score from 16 combined sleep elements and blood pressure (BP) category score from 3 combined BP elements (SBP, DBP, and heart rate).

The above-mentioned information can be observed in Figure 2.

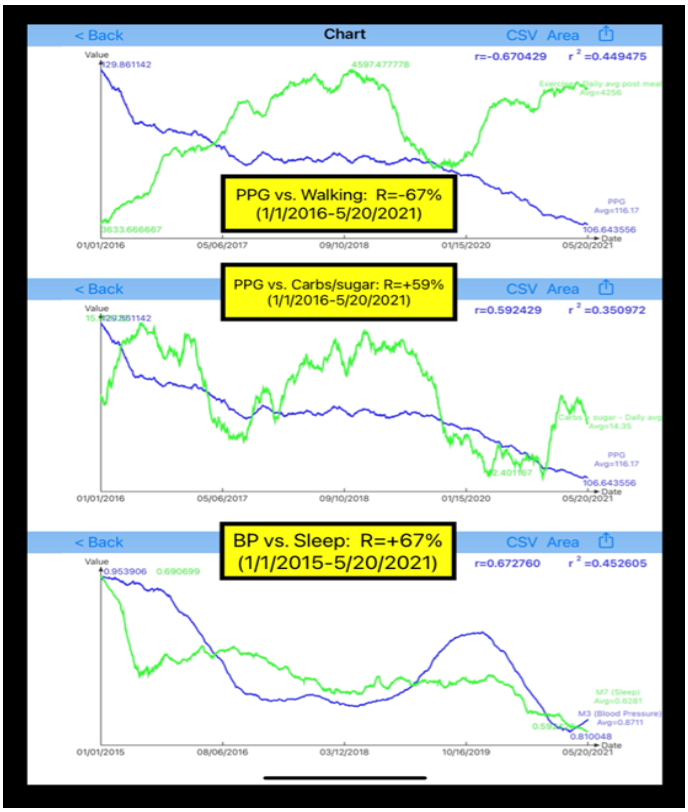

Figure 2: PPG vs. walking, PPG vs. carbs/sugar, and BP vs. sleep

Utilizing Young's modulus concept from linear elasticity of strength of material, he has developed his linear elastic glucose theory with a predicted PPG equation by combining above-mentioned inputs.

Predicted PPG =
(FPG or Weight * GH.f Modulus + Carbs/sugar grams * GH.p Modulus + Post-meal walking k-steps * GH.w Modulus)

Where GH.f, GH.p, GH.w are three distinctive glucose Modulus associated with fasting, carbs/sugar, and walking.

Daily Glucose =
0.29*FPG+0.38*PPG+0.33*IBG

Where IBG is the average in-between and pre-bed glucoses.

Above two sample equations have demonstrated the process of how to assemble different elements into a metabolism category.

Another example illustrates the stiffness value of 215 for his K5a health coefficient links his weight and food quantity along with the element M9a (food portion) of the food category M9 (see Figure 2). When his average food portion is at 81% level of his normal 100% portion, then his body weight would be ~173 lbs. (=0.81*215).

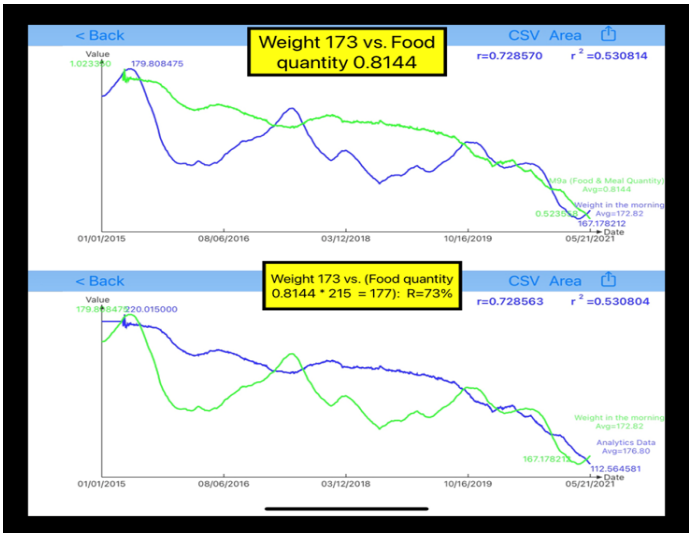

Figure 3: Weight and Food quantity

After completing the construction of each element within each category, he then explores the relationships of the medical conditions group (MCG) vs. each of the 6 lifestyle details, along with the lifestyle details group (LDG) vs. each of the 4 medical conditions, see both Figure 4 and Figure 5.

The following table summarizes the relationships via correlation coefficients of group vs. category:

From Figure 4:
MCG vs. food quality: 49%
MCG vs. water intake : 43%
MCG vs. exercise: 54%
MCG vs. sleep: 46%
*MCG vs. stress: 38% **
*MCG vs. daily routines: 32% **

From Figure 5:
LDG vs. weight: 69%
LDG vs. glucose: 86%
LDG vs. blood pressure: 74%

The key finding is that the combined lifestyle details group has direct and strong impacts on weight, glucose, and blood pressure (70% or above).

It should be noted that the two lower correlation items (* R=30% to 40%) in MCG vs. lifestyle categories are due to the author's extremely low stress and very regular daily life routines over the past 5.5 years since 2016. In addition, since the lipid data can only be obtained quarterly or semi-annually in hospitals or medical labs, they are not daily collected like the other biomarkers; therefore, a correlation analysis is quite difficult to perform

against other categories with daily inputs.

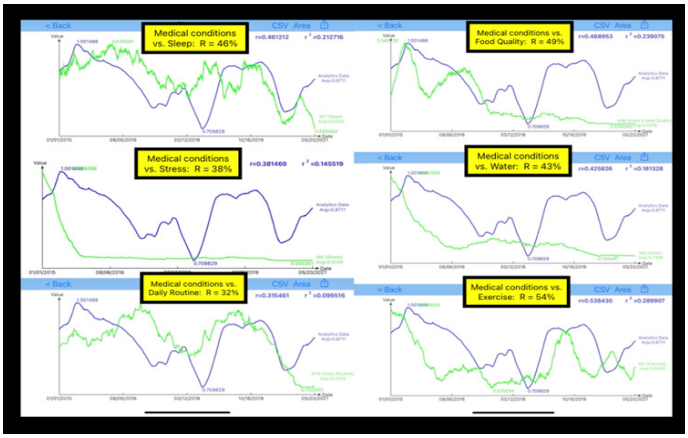

Figure 4: Medical conditions group (MCG) vs. 6 lifestyle details

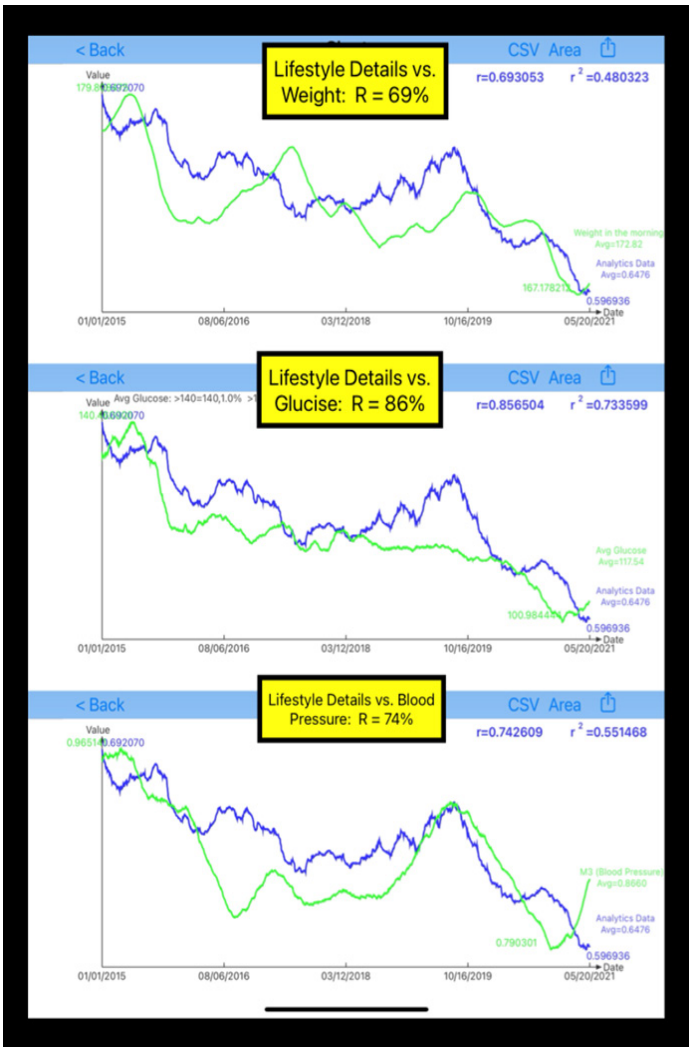

Figure 5: Lifestyle details group (LDG) vs. 3 medical conditions

The main focus of his medical research is to uncover T2D and its complications. Therefore, after discovering all of the related stiffness values i.e., the stiffness/health matrix and the macro-relationships of MCG vs. 6 lifestyle details along with the LDG vs. 3 medical conditions, his next step is to focus on HbA1C. The author performed a tremendous amount of glucose research work based on finger-pieced glucose and HbA1C using his own data since 2012. However, 4 finger-glucose readings per day and quarterly HbA1C value based on 90-days average glucoses can only describe the "mean or averaged" situations of the real glucose waves. These mean values provide some usefulness on studying diabetes but with certain limitations. However, an average amplitude of a wave will definitely miss some of vital information and significant characteristics of a waveform, such as the high prediction accuracy and the actual wave fluctuations, along with the excessive energy associated with the real glucose waveform and its real glucose fluctuation (GF) or glycemic variability (GV). For readers who are interested in reading more papers on these subjects, they can find the group of papers regarding "glucose energy and glucose fluctuation" in the reference section. The author has also defined two new HbA1C equations based on the continuous glucose monitor (CGM) sensor device collected glucose ("sensor glucose") readings at 96 data per day.

These two HbA1C equations are listed (see Figure 6):

Sensor HbA1C-1 =
(0.29*sensor eAG + 0.71*GF)/15.5

Sensor HbA1C-2 =
(sensor eAG)/18.9

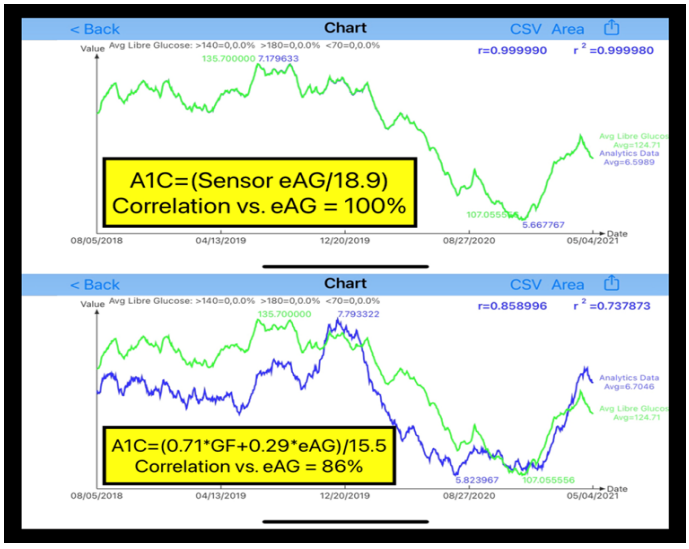

Figure 6: Sensor estimated average glucose (eAG) versus both of Sensor HbA1C-1 and Sensor HbA1C-2 (extremely high correlations)

Finally, the author utilizes various publicly-accepted biomarker values as his ***baseline of normalization process***. For example, these baselines include BMI 25, Glucose 120 mg/dL, Systolic blood pressure 120, Diastolic blood pressure 80, HDL 40, LDL 130, Total cholesterol 200, Triglycerides 150, body temperature 98.6F or 37C, weather temperature 72 °F or 22 °C, and more. These baseline numbers have different scales and units; therefore, he must "normalize" them into an identical structure scale to further process them and make comparisons. After the baseline values are converted into the same scale and unit which are located within the same "normalized range" between 0.4 (best score) to 1.6 (worst score), the combined metabolism index (MI) scores, including 4 medical condition scores and 6 lifestyle detail scores, will have a common "break-even line" at 0.735 or 73.5%. In other words, if any patients Mi (where i=1, 10) or

the total combined MI score are lower than 73.5%, then they are healthy. Likewise, it they are greater than 73.5%, then they are unhealthy. He further takes the 90-days moving average MI value to be defined as the general health status unit (GHSU) which has similar characteristics as MI.

After calculating the normalized values of each Mi (between 0.4 to 1.6 with a break-even level at 0.735 or 73.5%), the remaining task is to assemble the Mi (where i=1,10) together into a combined MI score. Instead of continuously dealing with some complicated partial differential equations and carrying a heavy numerical process burden from the assembly process using some equations of finite element engineering textbooks, the author decided to adopt a "***quick but not so dirty" approach from geometric algebra (GA), the "polygon area".***

Each Mi value indicates the calculated Mi value points on the 10 directional axes (i.e. 10 vectors with 10 vertices) of a ***10-dimensional polygon space***. The total area contained inside the 10 vertices of a polygon can provide a quick and useful indication of the combined effect of the 10 metabolism categories. In Figure 7, it shows the comparison of two randomly drawn 10-vertices polygon spaces: the blue polygon has the unhealthier metabolism with a larger calculated area, while the yellow polygon has the healthier metabolism with a smaller calculated area.

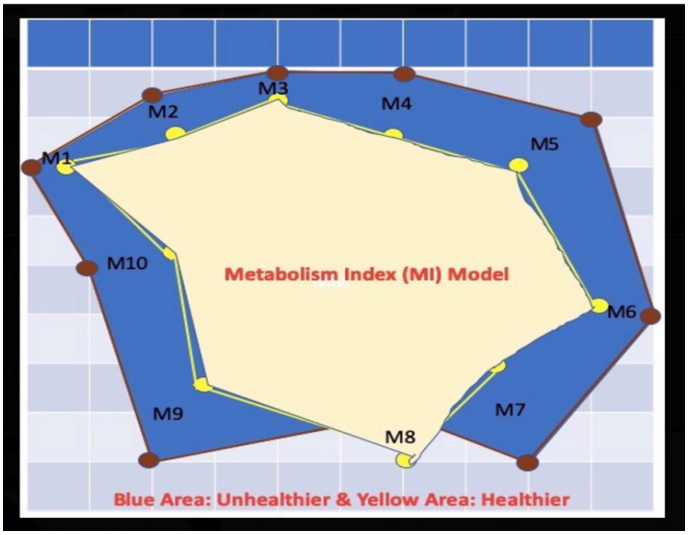

Figure 7: Metabolism polygon spaces (blue area is unhealthier and yellow area is healthier)

As an illustration shown in Figure 8, his personal metabolism results have indicated that he was extremely unhealthy (80%-110%) before 2013. The curve went through a sharp decline in 2014 resulted from his learned knowledge from his self-study and research on the subject of metabolism. After 2015, he became quite "healthy" (55%-70%). As of 5/20/2021, his MI is 63% and GHSU is 52% on that particular day. Overall, his average MI is 67% and average GHSU is 68% over a period of 9.5 years from 1/1/2012 through 5/20/2021. All of the biomarker data from his past health examinations have validated his calculated diagram of MI & GHSU, where all of his chronic disease conditions are well under control which is further demonstrated in the following data table. Here are the data comparison of 2010 vs. 2020:

Weight (BMI): 210 (31) / 170 (25) lbs.
Waistline: 44 / 33 inches
PPG: 350 / 108 mg/dL
FPG: 185 / 101 mg/dL
Daily glucose: 279 / 106 mg/dL
A1C: 10.0 / 6.2 %
ACR: 116 / 17 mg/mmol
Triglycerides: 1161 / 99 mg/dL

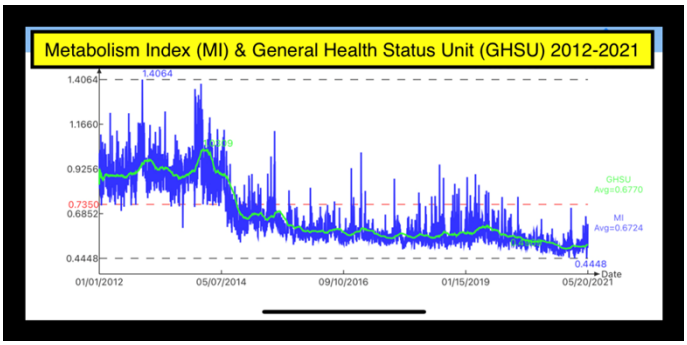

Figure 8: MI & GHSU 92012-2021

Furthermore, he utilizes the third order of ***perturbation theory*** from quantum mechanics to predict a complete 3-hour PPG waveform with a ***99% to 100% prediction accuracy.***

The following polynomial function is used to describe the general perturbation equation:

A = f(x)
*= A0 + (A1*x) + (A2*x**2)+(A3*x**3) + ... + (An*x**n)*

Where A is the perturbed glucose, Ai is the measured glucose at different time instant, and x is the chosen "perturbation factor" which may be some different formulas or ratios of "perturbation factor of x", in this case it is the carbs/sugar intake amount.

For this particular study, the author chooses this third-order perturbation equation, therefore, his Ai has i=1 to 3. Nw, the third-order perturbation equation above can then be expressed into the following simplified form:

A = f(x)
*= A0 + (A1*x) + (A2*x**2)+(A3*x**3)*

Or this three-orders interpolation perturbation equation can then be expressed in the following form:

Y = Y1 +
*(slope) * (Y2 - Y1) +*
*(slope**2) * (Y2-Y1) +*
*(slope**3) * (Y2-Y1)*

Where:
Y1 = original glucose Y-scale on time T1
Y2 = advanced glucose Y-scale on time T2

(Y2-Y1) = (Glucose Y at Time 2) - (Glucose Y at Time 1)

The perturbation factor, or ***slope,*** is an arbitrarily selected real parameter that controls the size of the perturbation. The author has chosen a function of x amount, e.g., the carbs/sugar intake amount, as the perturbation factor, or slope, which is defined by two formulas at below:

Slope A= (Selected Carbs - Low-bound Carbs) / (High-bound Carbs - Low-bound Carbs)

Slope B= (Selected Carbs) / (High-bound Carbs)

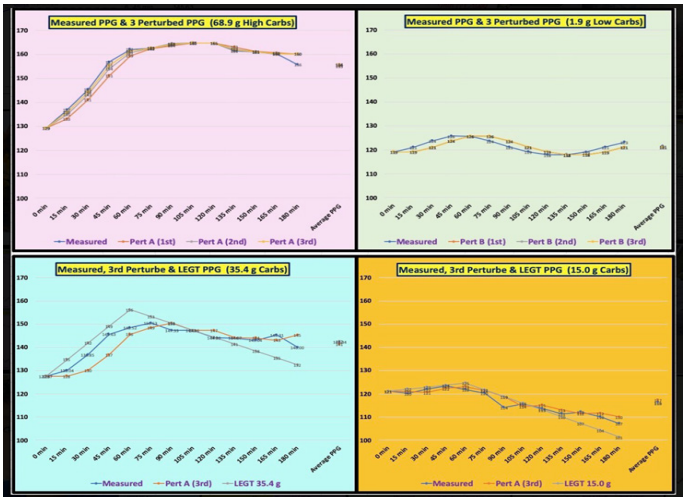

Figure 9: Combined PPG graphs of measured and perturbed waveforms for Carbs/sugar amounts of high-end of 6.8g, low-end of 1.9g, mean of 35.4g, and upper-end of recent data of 15.0g with a prediction accuracy of 99% - 100%

He also applies the Fast Fourier Transform (FFT) to convert a glucose wave from a time domain into a frequency domain in order to find the associated energy of glucose waves or glucose fluctuations which causes different degree of damages on various internal organs. Based on the information, he was able to conduct different risk assessment analyses of having diabetic complications related to heart, brain, kidney, pancreas, bladder, eyes, foot, nerves, etc. Furthermore, by utilizing his developed MI model, he is able to extend his research work into other related areas, such as deadly diseases of cancer and dementia, along with a more interesting area of geriatric and longevity.

Conclusion

This paper describes the author's selected approach of building a mathematical model of metabolism. It uses the topology concept, part of finite element engineering modeling technique, applicable theories and principles from physics and engineering, such as optical physics, energy theory, wave theory, linear elasticity, perturbation theory of quantum mechanics, and various computer science and AI tools to investigate and develop a rather complicated metabolism model in a highly quantitative manner. Optimistically and pleasantly, it has actually achieved certain high prediction accuracy in results based on a simple concept but rather general scope of "Metabolism".

References

The author has decided to list the references of this article by his published paper numbers instead of using the traditional format of references of other articles. All of these referenced papers were written by himself during the past 3.5 years.

Group 1 : MPM Methodology
Numbers: 397, 387, 386, 310

Group 2 : Metabolism Index
Numbers: 005, 009, 017, 025, 078, 087, 143, 224, 225, 235, 238, 240, 258, 259, 263, 278, 281, 287, 288, 292, 296, 298, 300, 316, 332

Group 3 : Linear Elastic Glucose Theory
Numbers: 440, 430, 429, 428, 427, 425, 424, 423, 422, 418, 417, 416, 415, 414, 413, 412, 411, 403, 402, 401, 396, 371, 370, 369, 367, 365, 364, 363, 362, 361, 360, 359, 358, 357, 356, 352, 350, 349, 346

Group 4 : Glucose Fluctuations (GF) or Glycemic Variability (GV)
Numbers: 451, 447, 446, 445, 436, 435, 432, 431, 403, 400, 390, 389

Group 5: Perturbation Theory
Numbers: 427, 426, 420, 154, 152

Group 6: Wave(TD) & Energy (FD)
Numbers: 447, 433, 428, 368, 272, 271, 270, 269, 267, 246, 120, 82, 40, 39, 36, 35