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Research paper

Predictive Modeling of GH Blunting Patterns in Aging and Exercise-Trained Individuals

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Abstract

This paper proposes a novel semiparametric method using Gaussian process smoothing to estimate failure rates in engineered systems. Unlike traditional models, it provides accurate estimates based on historical data without assuming specific failure rate patterns. Experiments using power system failure data demonstrate the method's accuracy and effectiveness compared to other models. The approach applies to various systems, including software reliability estimation. Additionally, mathematical results align well with the Gaussian process model, successfully identifying the peak of growth hormone deficiency over time.

Keywords: *Reliability; GH; Failure Patterns; Normal Process; Quasiparametric Model.*

1. Introduction

Reliability is crucial for intelligent grids and sustainable energy networks. A smart grid is a self-regulating power system that enables bidirectional electricity and data exchange among power stations, users, and intermediaries [9,18,19]. Accurately evaluating system reliability remains a challenge, with the failure rate serving as a key indicator. Traditionally, failure rates are estimated using historical data or equipment testing, followed by applying a failure distribution model such as the exponential or Weibull distribution. However, our findings suggest that these models may not be ideal for predicting power grid failures. Instead, we propose a quasiparametric model that does not assume a fixed or monotonic failure rate. By incorporating Gaussian smoothing, this model more closely aligns with actual failure patterns. When applied to power network data, it consistently outperformed traditional models in blind-test comparisons and real-world failure predictions [15], [16], [24].

2. Overview of reliability assessment

The failure rate refers to the count of letdowns within a population distributed by the overall operational duration under defined conditions over a specified period [17]. It is denoted as $\mu(t)$, while the reliability function $\Re(t)$ represents the chance of no letdown before time t. The letdown rate is then given by:

$$\mu(t) = \frac{\Re(t) - \Re(t+\delta t)}{\delta t . \Re(t)}$$

As δt approaches 0, μ Becomes the immediate letdown rate, also known as the risk function.

$$\mathfrak{H}(t) = \lim_{\delta t \to 0} \frac{\Re(t) - \Re(t+\delta t)}{\delta t . \Re(t)}$$

A letdown distribution $\mathfrak{F}(t)$ is an accumulative function representing the likelihood of letdown occurring up to and counting time t.

$$\mathfrak{F}(t) = 1 - \Re(t), t \geq 0$$

For an unbroken letdown rate, $\mathfrak{F}(t)$ is the vital of g(t).

$$\mathfrak{F}(t) = \int_0^t f(y)dy .$$

Then the hazard function becomes

$$\mathfrak{H}(t) = \frac{g(t)}{\mathfrak{K}(t)}$$

2.1. Mathematical failure rate models

For the Weibull distribution, the letdown density function g(t) and cumulative distribution function $\mathfrak{F}(t)$ are:

$$g(t;\mu,l) = \begin{cases} \frac{l}{\mu}\left(\frac{t}{\mu}\right)^{l-1} e^{-\left(\frac{t}{\mu}\right)^{l}} & t \geq 0 \\ 0, t < 0 \end{cases}$$

$$\mathfrak{F}(t;\mu,l) = \begin{cases} 1 - e^{-\left(\frac{t}{\mu}\right)^{l}}, & t \geq 0 \\ 0, & t < 0 \end{cases}$$

Where $l > 0$ is the shape parameter and $\mu > 0$ Is the scale parameter the hazard function when $t \geq 0$ is

$$\mathfrak{H}(t;\mu,l) = \frac{g(t;\mu,l)}{\mathfrak{K}(t;\mu,l)} = \frac{g(t;\mu,l)}{1-\mathfrak{F}(t;\mu,l)} = \frac{l}{\mu}\left(\frac{t}{\mu}\right)^{l-1}$$

When $l < 1$, the letdown amount reduces over time. When l=1, the letdown rate residues constant, making the Weibull distribution equivalent to the exponential distribution. When $l > 1$, the letdown proportion rises over time.

2.2. Quasiparametric model using normal smooth down technique

We estimate the longitudinal effect of a blip treatment on an all-or-nothing behavior at a precise time on systems with frequent events, like recoverable mechanical letdowns. The goal is to assess how the most recent treatment influences future failure rates. Extending Cox relapse with inside covariates, our method scales the underlying rate and incorporates Gaussian process smoothing. While applicable to any breakdown treatment, we emphasize failure events, offering a detailed explanation for "infant mortality" and enabling comparison with parametric representations like the Weibull distribution.

3. Probabilistic and deterioration-based analysis

We observe M units over [0, S], accounting for known missing periods. Let S be the event times, and j(t) the failing unit at t, with ties resolved randomly. For any unit $S - \tau_{s,j}$ Represents the previous outage time. If observation is independent of treatment and failure, no bias occurs [1,2]. We then use a non-parametric rate model.

$$\mu(t; j) = \mu_0(t)\varphi(s - \tau_{s,j});$$

$$\varphi(t) = e^{\xi(t)}$$

After 20 seconds, treatment increases failure likelihood by $\phi(20) = e^{\varsigma(20)}$ The full likelihood is then [3]:

$$m(\mu_0(t), \varphi(t)) = \left(\pi_{s\in S}\mu_0(t)\varphi(s - \tau_{s,j})\right) \times e^{-\int_0^S \sum_{i\,\epsilon\,\mathfrak{K}t)} \mu_0(t)\varphi(t - \tau_{s,j})\,dt}$$

Approximation follows dual steps [3]. First, μ_0 is shown to be zero for $t \notin S$, canceling out when conditioning on failure times. This simplifies estimating $\varphi(t) = e^{\varsigma(t)}$ Afterward, $\phi(t)$, the μ_0 It is estimated using a weighted non-parametric approach, but for simplicity, the author fits it as a constant per network via the method of moments. The model assumes prior treatments are “forgotten” upon a novel behavior. The link between hazard μ And the circulation function is detailed in [3]. The Cox framework helps reduce data, benefiting the Normal process setup, which scales as O (q^3). Further numerical stability and efficient cross-validation are achieved by binning. $s - \tau_s$ Into percentiles.

3.1. Gaussian process analysis

We put on a Gaussian process previously to $\varphi(t)$Using a circular base function. After marginalizing the prior [24] onto $s \epsilon S$, the $\varphi(t)$ Trails a Gaussian distribution with mean 0 and covariance matrix L, given by: $L_{t,t'} = d\, e^{-(t-t')^2/c}$
This marginal previous scattering is denoted as π. The parameters c and d represent the marginal difference and distinctive time scale, respectively. Based on training data performance, we set c=5.2 and $d=1.10^3$. Instead, cross-authentication with a grid exploration can provide approximate estimates for these parameters [3], [24]. The Gaussian process prior significantly improves the smoothed fit compared to the unsmoothed version.

4. Applications

Elderly individuals experience a reduction in muscle strength and exercise performance due to both decreased physical activity and age-related physiological decline. Studies have shown that aging [25] and growth hormone (GH) deficiency [13] are each associated with

reduced protein synthesis and a loss of fat-free mass. GH secretion begins to decrease after the age of 40 [10,26], and age-related GH deficiency has been well established, with treatment shown to improve lean body mass [4,14]. However, the responsiveness of somatotropic cells, which are responsible for GH production, varies among individuals [6], indicating that not all older adults experience the same degree of hormonal decline.

Exercise is a potent stimulus for GH secretion, with levels increasing during both aerobic and resistance training and peaking at approximately 70% of VO_2max [5], [12]. This hormonal surge contributes to muscle protein synthesis and tissue repair. Nevertheless, the GH response to exercise is diminished with aging [11], [23], suggesting that older adults may not experience the same magnitude of benefit as younger individuals. Despite this, elderly individuals who maintain a regular training routine tend to preserve better muscle mass and strength compared to their sedentary peers, highlighting the protective role of physical activity.

While regular training may influence anabolic hormones and growth factors, its precise effects on GH and insulin-like growth factor I (IGF-I) remain inconclusive [20 - 22]. Some studies report increases in these hormones with consistent training, while others find minimal or no significant changes. This inconsistency could be due to variations in exercise type, intensity, and individual physiological differences. Understanding these hormonal responses is crucial for developing training programs that maximize health and performance benefits in aging populations.

Most research in this area focuses on adults aged 60–70, even though the decline in GH secretion begins around the age of 40 [10], [11]. This represents a gap in the literature regarding middle-aged individuals, who may already be experiencing reduced GH production but are not typically included in intervention studies. The present study aims to investigate whether the reduced GH response observed in elderly men also occurs in middle-aged men and to assess whether endurance training can help maintain or improve GH secretion in this age group.

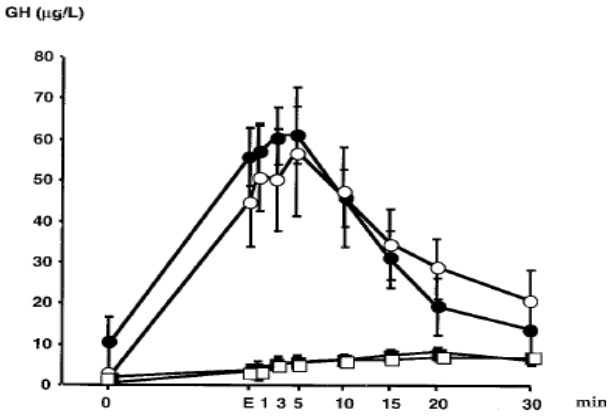

Fig. 4.1: GH Response to Maximal Exercise and Training Adaptation in Athletes.

A significant difference in the GH response to exercise was observed between the two groups (Fig. 4.1). In the younger group (Y), GH levels increased approximately sevenfold, reaching their peak between the end of exercise and the 10th minute of recovery. In contrast, the middle-aged group (M) showed a delayed peak (15–30 minutes) that was markedly lower than in Y, both before (8.2 ± 1.2 vs. 57.2 ± 15.4 µg/L; $P < 0.01$) and after training (6.6 ± 1.1 vs. 61.1 ± 12.8 µg/L; $P < 0.01$) [8], [12], [14].

Mean GH peaks and integrated responses (AUC) were significantly lower in M compared to Y and remained unchanged after the training program (209.3 ± 67 vs. 1568.6 ± 290.2 µg/L; $P < 0.001$). No significant correlation was found between GH peaks, AUC, BMI, or FM. Although IGF-I levels were lower in M, they remained within the normal range and showed only slight, non-significant reductions following training [4 - 7].

5. Further discussion

We analyzed the GH reaction to maximal workout in young and early middle-aged individuals before and after four months of survival training. Our main finding revealed that middle-aged participants exhibited a significantly lower GH response than younger ones, and training did not improve this response.GH secretion declines with age, with a progressive reduction in spontaneous GH pulses starting in the third decade. While GH response to pharmacological stimulation is inconsistent in older adults, exercise is a strong GH stimulus. Previous studies confirm reduced GH response in elderly individuals during aerobic and resistance exercise, and our results extend this finding to early middle age. Despite expectations of only a slight decline, the GH response in middle-aged subjects was markedly lower than in young subjects. This reduction was not influenced by exercise intensity, blood lactate, or glucose levels. Additionally, preparation did not alter basal IGF-I levels or GH reaction in either group. While the impact of physical activity on GH secretion remains debated in older adults, our findings suggest that the blunted GH response is more related to aging than activity level. This may be due to increased hypothalamic somatostatin or reduced GHRH secretion or action, which plays a key role in exercise-induced GH release.

6. Mathematical results

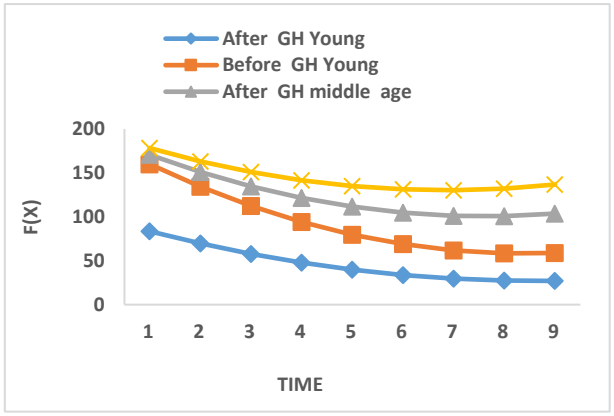

Fig. 6.1: Probability Density Function of GH Reaction to Implementation and Recovery in Athletes.

Figure 6.1 illustrates the distribution of Growth Hormone (GH) responses in athletes after the implementation of a specific medical or training intervention and during the subsequent recovery phase. It represents the likelihood of observing various GH concentration levels over time, using a probability density function (PDF) derived from the experimental or clinical data shown in Medical Figure 4.1.

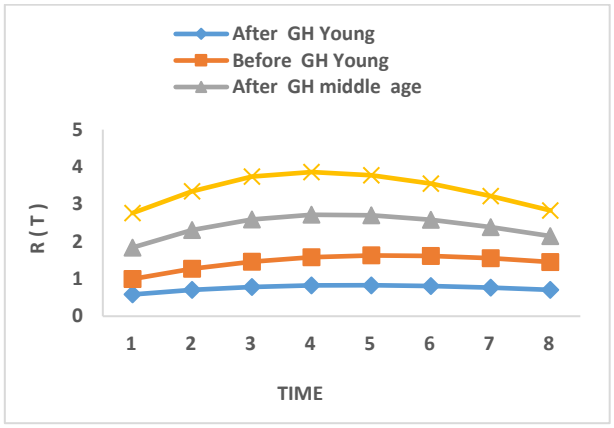

Fig. 6.2: Hazard Rate of GH Response to Exercise and Recovery in Athletes.

Figure 6.2 illustrates that the hazard rate in this context is a statistical measure that indicates the instantaneous risk or likelihood that a certain event occurs at a specific time, given that it has not occurred before. For physiological data, the hazard rate is often used to understand how quickly a biological response (such as GH elevation or decline) happens after a stimulus, here, exercise, and during the recovery period.

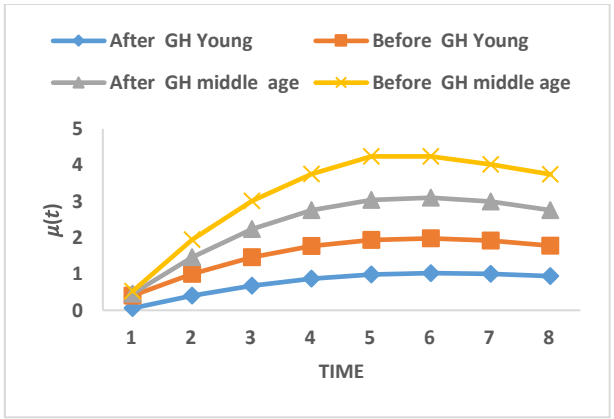

Fig. 6.3: Gaussian Process for GH Response to Exercise and Recovery in Athletes.

Figure 6.3 illustrates that the Gaussian Process is a statistical modeling framework used to estimate an unknown function from observed data, with uncertainty quantification. In this context, the Gaussian Process is applied to model Growth Hormone (GH) concentration over time during exercise and recovery, using observed samples from athletes. A Gaussian Process treats the GH response curve as a distribution over functions, where each point in time has a predicted mean and confidence interval (uncertainty band).

7. Conclusion

This paper introduces a novel method for approximating failure rates using a quasiparametric model with Normal process smoothing. By leveraging historical data, the approach delivers precise estimations without assuming a fixed failure rate pattern. Empirical studies on control system failure data demonstrate its superior performance compared to existing models. Moreover, this method applies to reliability estimation across various systems, including software and hardware components. Additionally, the mathematical results in Figure (6.1, 6.2, 6.3) closely align with the Normal process, accurately identifying the peak of Growth Hormone deficiency, which may aid medical professionals.

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References

[1] Amin S.M.,(2010)" U.S. electrical grid gets less reliable",IEEE Spectrum ,Jan. https://doi.org/10.1109/MSPEC.2011.5676396.
[2] Andersen P.K, Borgan O, Gill R.D, Keiding .N, (1995)Statistical Models based on Counting Processes, Springer.
[3] Bennett RM,Clark SR,Walczyk J(1998): A randomized double blind, placebo – controlled study of growth hormone in the treatment of fibromyalgia.Anj Med,104:227 – 231. https://doi.org/10.1016/S0002-9343(97)00351-3.
[4] Binnerts A, Wilson JHP, Lamberts SWJ. (1988) The effects of human growth hormone administration in elderly adults with recent weight loss. J Clin Endocrinol Metab 67:1312 – 1216. https://doi.org/10.1210/jcem-67-6-1312.
[5] Borst SE, Millard WJ, Lowenthal DT. (1994) Growth hormone, exercise, and aging; the future of therapy for the frail elderly. J Am Geriatr Soc. 42:528-535. https://doi.org/10.1111/j.1532-5415.1994.tb04976.x.
[6] Corpas E, Harman S & Blackman M. (1993) Human growth hormone and human aging. Endocrine Reviews 14 20-38. https://doi.org/10.1210/edrv-14-1-20.
[7] Florini JR.(1987) Hormonal control of muscle growth. Muscle Nerve. 10: 577-598. https://doi.org/10.1002/mus.880100702.
[8] Frontera WR, Meredith CN, O'Reilly KP, Knuttgen HG, Evans WJ. (1988) Strength conditioning in older men: skeletal muscle hypertrophy and improved function. J Appl Physiol. 64: 1038-104 4. https://doi.org/10.1152/jappl.1988.64.3.1038.
[9] Federal Smart (2010) Grid Task Force, Smart grid basics available: http://www.smartgrid.gov/basics.
[10] Finkelstein J, Roffwarg H, Boyar P, Kream J, Hellman L. (1972) Age-related changes in the twenty-four hour spontaneous secretion of growth hormone in normal individuals. JClin Endocrinol Metab. 35:665-670. https://doi.org/10.1210/jcem-35-5-665.
[11] Hagberg JM, Seals DR, Yerg JE, et al. (1988) Metabolic responses to exercise in young and old athletes and sedentary men. J Appl Physiol. 65:900-908. https://doi.org/10.1152/jappl.1988.65.2.900.
[12] Luger A, Watschinger B , Deuster P, Svoboda T, Clodi M, Chrousos GP. (1992) Plasma growth hormone and prolactin responses to graded levels of acute exercise and to a lactate infusion. Neuroendocrinology. 56:112-117. https://doi.org/10.1159/000126912.
[13] Jorgensen JO, Pedersen SA, Thuesen L, et al. (1989) Beneficial effects of growth hormone treatment in GH-deficient adults. Lancet 1:1221-1225. https://doi.org/10.1016/S0140-6736(89)92328-3.
[14] Jorge Angel Ascacio-Martinez and Hugo Alberto Barrera-Saldana (2012)" Genetic Engineering basics, new applications and responsibilities", ISBN 978-953-307-790-1.
[15] Kalaiselvi . R and Manickam, A(2021) A Mathematical Skew-Logistic Model for Circadian Gene Expression Regulates Pulsatile Gonadotropin-Releasing Hormone (Gnrh) Secretory Patterns In The Hypothalamic Gnrh-Secreting Gt1-7 Cell Line" South East Asian Journal of Mathematics and Mathematical Sciences, Volume.17, ISSN:0972-7752(P) 2582-0850(E).
[16] Lakshmi.S and Manickam.A.(2014) "Mathematical model for finding the maximum value of growth hormone (GH) deficiency in patients with fibromyalgia by using Gaussian process". IOSR Journal of Engineering (IOSRJEN). ISSN(e):2250-3021, ISSN(p):2278-8719. Vol.04, Issue 04 (April), Vol. Pp 08-15. https://doi.org/10.9790/3021-04460815.
[17] Little wood B and Verrall J.L.,(1974) "A Bayesian Reliability Model with a Stochastically Monotone failure rate", IEEE Transactions on Reliability, vol, R-23, No: 2, pp. 108 – 114. https://doi.org/10.1109/TR.1974.5215217.
[18] Leema Rose. A and Manickam, A.(2021), "A Mathematical model for Enduring effect of childhood maltreatment on cortisol and heart rate responses to stress using Log-Normal Distributions" South East Asian Journal of Mathematics and Mathematical Sciences, Volume. 17 . ISSN:0972-7752(P) 2582-0850(E).
[19] A. Manickam*, A. Benevatho Jaison, D. Lakshmi, Ram Singh, and C. T. Dora Pravina,(2024) A mathematical study of the adrenocorticotropic hormone as a regulator of human gene expression in adrenal glands. Computational and Mathematical Biophysics 2024; https://doi.org/10.1515/cmb-2023-0122.
[20] A. Manickam, M. Kavitha, A. Benevatho Jaison, Arvind Kumar Singh (2024) A fractional-order mathematical model of Banana Xanthomonas Wilt disease using Caputo derivatives. Volume 5 issue 1 pp 136-156. *Contemporary Mathematics* ISSN: 2705-1064. https://doi.org/10.37256/cm.5120242479.
[21] A. Manickam Pushpendra Kumar K. Dasunaidu V. Govindaraj and Dheeraj Kumar Joshi (2022) A stochastic SIR model for analysis of testosterone 7 suppression of CRH-stimulated cortisol in men. International Journal of Modeling, Simulation, and Scientific Computing 2250021 (7 pages) https://doi.org/10.1142/S1793962322500210.
[22] A.Manickam R.L.Naidu and S.Indrakala(2020) " A Study on Weibull-G Exponential Distribution Model for Secretion of Gn rh In Beef Cows"Advances in Mathematics: Scientific Journal 8 no.9 7477–7482 ISSN 1857-8365 printed version ISSN 1857-8438 electronic version. https://doi.org/10.37418/amsj.9.9.94.
[23] Pyka G, Wiswell RA, Marcus R. (1992) Age-dependent effect of resistance exercise on growth hormone secretion in people. J clin Endocrinol Metab. 75: 404-407. (223) https://doi.org/10.1210/jcem.75.2.1639942.
[24] Rasmussen C.E and Williams C.K.I,(2006) Gaussian Processes for Machine Learning,MIT Press. http.s://doi.org/10.7551/mitpress/3206.001.0001
[25] Rudman D. (1985) Growth hormone, body composition and aging. J Am Geriatr Soc. 33:800-807. https://doi.org/10.1111/j.1532-5415.1985.tb04195.x.
[26] Zadik Z, Chalew SA, McCarter RJ, Meistas M, Kowarski AA, (1985) The influence of age on the 24-hour integrated concentration of growth hormone in normal individuals J.Clin Endocrinol Metab. 60:513-516. https://doi.org/10.1210/jcem-60-3-513.