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Smart Reliability Estimation Via ANN–ABC Optimization: A Novel Approach to Inverse Weibull Process Under NHPP

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Abstract: In this work, a new intelligent hybrid estimation framework is proposed to model the time-dependent failure behavior of a repairable system. The model adopts an Artificial Neural Network by applying the Artificial Bee Colony (ANN-ABC) algorithm. It also combines the Inverse Weibull Process (IWP) with the Nonhomogeneous Poisson Process (NHPP) framework. The study compared the traditional Maximum Likelihood Estimate (MLE) model with the proposed hybrid algorithm using simulation. The results showed that the ANN-ABC model has lower Root Mean Square Error (RMSE) and Bayesian Information Criterion (BIC) when a moderate-to-large dataset is used. In addition, the proposed model was validated using real clinical data from 299 heart failure patients to predict the survival likelihood. The results validate that the proposed hybrid intelligent methods can be used to support AI-driven reliability modelling for complex data driven systems such as monitoring, predictive maintenance, and intelligent healthcare systems due to their superior support in the precise estimation of failure intensities. This contributes to SDG 3 (Good Health and Well-Being) and SDG 9 (Industry, Innovation and Infrastructure) by enabling more reliable intelligent healthcare and resilient cyber-physical infrastructures.

Keywords: Inverse Weibull Process (IWP); Non-Homogeneous Poisson Process (NHPP); Artificial Neural Network (ANN); Artificial Bee Colony (ABC); Reliability Modeling; Predictive Maintenance; Failure Data Analytics.

1. Introduction

Predictive maintenance optimization and close analysis of failures in repairable systems and smart monitoring, particularly in safety-bound fields like healthcare, power systems, and infrastructure involving the IoT-based system, require reliability models drastically. The Non-Homogeneous Poisson Process (NHPP) is such a widely-used modeling framework because it allows one to model time-varying failure rates. In this regard, the Inverse Weibull Process (IWP) gives an adaptable solution of modeling-tired processes in systems where hazards decrease at increasing speeds and loss of life very early on in life. [1, 2]. While, the rapid deployment of autonomous and connected vehicles brings substantial opportunities for safer and more efficient transportation, but also introduces critical cybersecurity and reliability challenges due to their reliance on advanced electronics, connectivity, and artificial intelligence. Recent studies on cybersecurity in autonomous vehicles highlight evolving threats such as remote hacking, sensor manipulation, data breaches, and denial-of-service attacks, underscoring the need for more accurate, data-driven reliability modelling frameworks in safety-critical systems. [32].

Existing methods that apply to traditional estimation, e.g., Maximum Likelihood Estimation (MLE), can prove

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incomplete in nonlinear setting and in real-world tasks, because of assumptions of large samples or limits of computation. To deal with these, a hybrid intelligent method which incorporates Artificial Neural Networks (ANNs) and Artificial Bee Colony (ABC) optimization algorithm has been proposed by this study. This is a method that seeks to enhance the accuracy of estimates and reduce the computing efficiency especially in small-to-medium data settings. This development helps in establishing intelligent estimation frameworks in complex and time-varying failure modeling that boasts of admirable prospects in smart healthcare, anomaly detection, and secure Internet tools and systems.

The current study aimed at parameter estimation of IWP to reflect variation in failure rate over time [3]. Two estimation schemes are used MLE and ANN-ABC. They both are based on frequent and probabilistic models. In reliability growth analysis it is very essential to understand whether there is an improvement trend or rather a trend which is getting worse. The inter-failure interval is increasing, which means improvement and the opposite shortening of inter-failure means degradation. Because of the time varying intensity function, the NHPP is good at modelling these dynamics. Renewal processes, in contrast, suppose that the random variables governing the times between failures are identically distributed and independent, but otherwise are very general: the case of exponentially distributed inter-arrival times gives a Homogeneous Poisson Process [4, 5].

The current work will give a contribution to reliability modeling because it compares empirical and machine learning estimators based on IWP to diversify the approach to predictive maintenance and failure prediction. Many fuzzy reliability estimation methodologies of estimation procedures have been studied, as well as their statistical counterparts. These papers have introduced one approach that brought the idea of frailty-based modeling of repairable systems with dependent failure times assuming the perfect repairs. The estimation of the parameters and a validation exercise of the real data of sugarcane harvesters and dump trucks were carried out to capture unobserved heterogeneity and failure dependence which helps in distributing the maintenance decision. Additions to be made in the future involve the addition of imperfect repairing and Bayesian inference [6, 7].

The Bayes adjustments of the change-point in a Weibull-intensity NHPP provided working of MCMC and model-based choice through the Bayes factor and DIC [8]. The survival model based on Burr Type XII distribution, MLE, and SVM was used as a hybrid model in predicting the survival of cancer [9]. Telecommunications and healthcare are some other fields where the application of NHPP models has been undertaken. A different study constructed fuzzy inverse Gompertz model-based survival to compare the classical and artificial intelligence estimators in terms of their performance in simulated and real data [10-12].

2 Inverse Weibull Process (Proposed Model)

The IWP distribution is flexible and analytically tractable which makes it appropriate to use in life-testing and analysis of reliability data. IWP has been built on the fact that it can be used to model time dependent failure rates under non-homogeneous Poisson processes. As the IWP distribution contains a unimodal probability density, being an exponential family member, the distribution can be useful in predicting complex system failures, which can be applied in manufacturing, engineering and health care fields [13].

$$f(t) = \lambda(t)e^{-m(t_0)}, 0 < t < \infty \quad (1)$$

where $f(t)$ is the probability density function of the time until the first failure/event occurs, evaluated at time t, $\lambda(t)$ is the intensity function of the NHPP at time t, indicating the instantaneous rate at which events (e.g., failures) are expected to occur. And $m(t)$ is the mean value function (MVF) evaluated at time t_0, representing the expected cumulative number of events from time 0 up to time t_0. Proposed the time rate of occurrence, denoted as $\lambda(t)$, the new process is defined by the following equation [14, 15]:

$$\lambda(\mathrm{t}) = \frac{k}{\beta}\left(\frac{t}{\beta}\right)^{k-1}, 0 < t < \infty\ , \ \beta,\ k > 0 \quad (2)$$

where t represents time, and the parameters β and k are positive constants. The mean value function is expressed as follows:

$$m(\mathrm{t}) = \int_0^{\mathrm{t}} \lambda(u)\, du\, , 0 < t < \infty, \quad (3)$$

$$= \int_0^{\mathrm{t}} \frac{k}{\beta}\left(\frac{t}{\beta}\right)^{k-1} du,$$

$$= \left(\frac{t}{\beta}\right)^{k}, 0 \le t \le t_0, \quad (4)$$

we will substitute Eqs. (2) and (4) into Eq. (1), The Inverse Weibull process is obtained through the pdf, denoted by [16, 17]:

$$f(t) = \frac{k}{\beta}\left(\frac{t}{\beta}\right)^{k-1} e^{-\left(\frac{t}{\beta}\right)^{k}},\ t > 0, \quad (5)$$

where β and k controls the shape of the inverse Weibull intensity, acting as a scale parameter. It is important to correctly estimate β and k, since it shapes how well the model works and how it describes the data. Proper calculation of this parameter helps the IWP perform more successfully in studying reliability.

3 Methods of Estimations

The Inverse Weibull Process has several kinds of parameter estimation. This paper evaluates both the performance of the MLE and ANN-ABC on many aspects and testability.

3.1 Maximum Likelihood Method (MLE)

One of the cornerstones of the study of parameter estimation in stochastic models is known as MLE which has generally been found useful because apart from being consistent, unbiased in the large sample limits, and efficient with standard conditions, it is also simple to compute as well. It gives estimates that best describe the underlying probabilistic structure by minimizing the Kullback-Leibler divergence between the likelihood and parameter values it attempts to find which maximize that likelihood, given observed data. The joint probability density of time points at which events are observed, Nonhomogeneous Poisson Processes (NHPPs) whose intensity functions are functions of time. $(t_1, t_2, \dots, t_n)$ is given by Eq. (5) [18,19]:

$$f(t_1, t_2, \dots, t_n) = \prod_{i=1}^{n} \lambda(t_i) e^{-m(t_0)}. \quad (6)$$

From Eq. (5), we substitute it into Eq. (6) to get the joint probability function:

$$f(t_1, t_2, \dots, t_n) = \prod_{i=1}^{n} \frac{k}{\beta}\left(\frac{t_i}{\beta}\right)^{k-1} e^{-\left(\frac{t_0}{\beta}\right)^k}. \quad (7)$$

The Likelihood function form Eq. (7) for the period (0, t].

$$L = \prod_{i=1}^{n} \frac{k}{\beta}\left(\frac{t_i}{\beta}\right)^{k-1} e^{-\left(\frac{t_0}{\beta}\right)^k}. \quad (8)$$

The log-likelihood function is expressed as follows:

$$\ln L = n \ln(k) - n \ln\beta - (k-1)\sum_{i=1}^{n} \ln\left(\frac{t_i}{\beta}\right) - n\left(\frac{t_0}{\beta}\right)^k, \quad (9)$$

hence, deriving Eq. (9) with respect to parameter β, we get:

$$\frac{\partial \ln L}{\partial \beta} = -\frac{n}{\beta} + \frac{n(k-1)}{\beta} - \frac{k}{\beta}\left(\frac{t_0}{\beta}\right)^k$$
(10)

Deriving equation (9) with respect to parameter k will be:

$$\frac{\partial \ln L}{\partial k} = -\frac{n}{k} - \sum_{i=1}^{n} \ln\left(\frac{t_i}{\beta}\right) - n\left(\frac{t_0}{\beta}\right)^k \ln\left(\frac{t_0}{\beta}\right). \quad (11)$$

Because of the nonlinearity of the likelihood equations that are very high, the conventional analytical methods cannot be used to estimate the parameters β and k. Rather numerical methods, like Newton-Raphson, or EM algorithm must be applied to solve the system iteratively and to provide maximum likelihood estimates.

3.2 Modified Artificial Neural Network (MANN)

Artificial Neural Network (ANN) is a network of interconnected neurons; each with related weight and bias. As soon as the network structure is determined, the next process is to train optimal weights and biases such that predictions are more accurate. This is done through various techniques; where the ABC algorithm is utilized in this study to improve the training performance. Thorough description of ABC is made in [20] and there is a detailed implementation which is applicable in this work in [21]. Implementation in MATLAB is also available.

3.2.1 Proposed Artificial Neural Networks Training Approach Using ABC Algorithm

Among the most commonly used artificial intelligence tools are the Artificial Neural Networks (ANNs) whose applications cut across the fields of classification, prediction and pattern recognition. With well-adjusted weights and parameter, ANNs are capable of doing millions of operations quite efficiently. Optimization techniques it has traditionally been used to train through optimization, typically gradient descent; in many cases the optimization algorithm may get stuck in local minima a phenomenon dependent on the topology of the loss function. With the aim of solving this shortcoming, a nature-inspired optimization method, the ABC algorithm is offered to train ANNs instead of the standard optimization method. The conceptual similarity of the ABC algorithm with the Firefly Algorithm is that individuals (e.g. bees or fireflies) are attracted to others with respect to intensity in ABC and this translates to fitness [22-24]. ANN training with ABC normally takes place in eight states as outlined in:

Step 1: Initialization ANN

- Initialize an artificial neural network with a specified number of hidden layers, neurons, and weights.
- The ANN is used to model the system or predict the output.

Step 2: Initialize ABC

- Initialize the ABC algorithm with a population of artificial bees and the number of iterations with $i_{max} = 100$ where each bee represents a potential solution to the optimization problem.
- Each bee is assigned a random position X in the search space, which corresponds to the weights and biases of the ANN.
- Determine the objective function that represents the Eqs. (10) and (11) & Fitness function is the

$$RMSE = \sqrt{\frac{\sum_{i=1}^{Q}(\hat{\gamma}_i - \gamma)^2}{Q}}.$$

Step 3: Evaluate ANN

- Evaluate the fitness of each bee (solution) using the ANN.
- The fitness function is defined as the negative of the root mean squared error (RMSE) between the predicted output of the ANN and the target output.

Step 4: Employed Bees Phase

Each employed bee searches for a new food source (solution) in the neighborhood of its current position using the following equation:

$$v_{ij} = x_{ij} + \pi_{ij} * (x_{ij} - x_{kj}) \quad (12)$$

where v_{ij} is the new food source (solution), x_{ij} is the current position of the employed bee, π_{ij} is a random number between -1 and 1, and x_{kj} is the position of a randomly selected bee k.

Step 5: Onlooker Bees Phase

Each onlooker bee selects a food source (solution) from the employed bees based on the probability.

Step 6: Scout Bees Phase

If a food source (solution) is abandoned, a scout bee is sent to search for a new food source using the following equation:

$$x_{ij} = x_{min,j} + rand(0,1) * (x_{max,j} - x_{min,j}) \quad (13)$$

where x_{ij} is the new food source (solution), $x_{max,j}$ *and* $x_{min,j}$ are the minimum and maximum bounds of the j^{th}.

Step 7: Once the Weights and Biases Have Been Updated, Check the MSE

- If the $MSE_{new} \leq MSE_{old}$ then choose $M_{new} = M_{old}/B$ and go to step 2.
- Otherwise choose $M_{new} = M_{old} * B$ and go to step 3.

Step 8: Iteration

Repeat steps 3-7 until a stopping criterion is reached.

4 Simulation

Simulation is an important feature in the examination of systems and processes in that real or hypothetical operations are modeled mathematically or through computer derivation. Its versatility allows researchers to see the effect of parameters and test hypotheses without any restrictions posed by having to physically conduct an experiment. Simulation is extremely crucial in a wide range of situations in which empirical tests are time-consuming, expensive, or simply impractical. It can provide information about system behavior by means of a systematic selection of input variations, and be used to validate a model used in such a wide variety of fields as engineering, economics, and software systems [17, 23].

Stage I: Model Initialization and Parameter Specification

The first stage is ground technique, in which one finds the main hypotheses and chooses the parameter values that characterize the further simulation process. It has three sequential elements necessary to configure processes.

Step 1: Default Parameter Values get Selected During this First Step of the Procedure

The algorithm of simulation starts on default values of parameters of the Inverse Weibull process realized on past empirical researches and solid validation. Out of several configurations that were tested, two sets of parameters performed better.

- **Set 1:** $\beta = 0.6;\ k = 1.6.$

These parameters respectively define the shape, scale, location, and additional distributional characteristics necessary for generating synthetic data that closely resemble the theoretical behavior of the Inverse Weibull Distribution as shown in the table 1.

Step 2: Determination of Sample Sizes

Different sample sizes of small medium and large datasets successfully measure the stability and performance of the estimators during the simulation.

- $n = 50;\ 100;\ 500.$

This stratification allows for rigorous analysis of estimator sensitivity and efficiency under varying data volumes.

Stage II: Random Data Generation via Inverse Transformation

This stage involves the generation of pseudo-random data points that follow the probability distribution function of the Inverse Weibull Process, utilizing the Inverse Transform Sampling Method.

Step 1: Generation of Uniform Random Variables

Let

$$u_i \sim U(0,1), i = 0,1,2,\dots,n. \quad (14)$$

MATLAB provides the built-in rand function to produce Independent Identical Distributed (IID) random variables distributed uniformly from the interval $(0,1)$ during this stage.

Step 2: Transformation to Inverse Rayleigh Distribution Data

The generated uniform variables are transformed into data that follow the Inverse Weibull Process via the Inverse Cumulative Distribution Function (CDF). This transformation leverages the known CDF of the Inverse Weibull Distribution, denoted as Eq. (1) in the study, and applies the inverse mapping: $x_i = F^{-1}(y)$, This simplifies to:

$$t_i = \sqrt{\frac{u}{-\alpha^2}}, i = 0,1,2,\dots,n. \quad (15)$$

This procedure ensures that the synthetic dataset accurately represents the statistical characteristics of the Inverse Weibull Process under study.

Stage III: Parameter Estimation

The last step in the simulation model is parameter estimation of the Inverse Weibull distribution in Software Reliability Growth Models (SRGMs). The method used in this phase is to use several estimation methods on the entire observation duration so that there is a guarantee of statistical accuracy as well as prediction reliability. The next techniques are used: Maximum Likelihood Estimation, and Artificial Neural

Network with Artificial Bee Colony algorithm (ANN-ABC).

Stage IV:

The optimal estimation method was identified based on the comparison metric Root Mean Squared Error (RMSE), evaluated across the estimation of the probability density function.

Stage V:

Experiment is repeated 1000 times.

Stage VI:

Compute the Root Mean Square Error (RMSE) for each observation t_i, based on the estimated distribution parameters c and k.

$$RMS(\hat{\beta}) = \sqrt{\frac{\sum_{i=1}^{Q}(\widehat{\beta_i}-\beta_i)^2}{Q}} \quad (16)$$

Stage VII:

Schwarz Information Criterion (SIC/BIC): to compare models:

Compared to the Root Mean Square Error (RMSE), this paper adds the Schwarz Information Criterion (SIC), as also known as the Bayesian Information Criterion (BIC), to gauge model performance through penalization of model complexity. The BIC of this is calculated as [25- 28]:

$$BIC = -2\,log\,L(\hat{\theta}) + k\,log(n), \quad (17)$$

where $L(\hat{\theta})$ represents the maximum likelihood of the model and k is the number of free parameters, n is the sample size. The criteria are a tradeoff between model fit and parsimony. In the case of both the MLE as well as the Bayesian estimators, there was the computation of BIC based on both simulated as well as real data. The model with the least BIC is taken as the most desirable and provides the best trade-off between the explanatory power and complexity.

Table 1: The simulated RMSE and BIC for the MLE and Artificial Neural network-ABC for IWP

n	parameters	RMSE		BIC	
		MLE	ANN-ABC	MLE	ANN − ABC
50	$\beta = 0.6; k = 1.6$	29.397	27.569*	19.287	16.469*
	$\beta = 1.6; k = 0.6$	29.298	21.563*	19.198	11.363*
100	$\beta = 0.6; k = 1.6$	18.914	18.321*	28.814	17.211*
	$\beta = 1.6; k = 0.6$	18.385	15.041*	28.495	14.031*
500	$\beta = 0.6; k = 1.6$	13.061	12.853*	23.051	11.753*
	$\beta = 1.6; k = 0.6$	10.844	10.093*	20.734	9.083*

The numerical results shown in Table 1 are indicative of the estimates of the model parameters of the IWP that was estimated using the MLE and other ANN-ABC techniques. A comparison of the models using the (RMSE) and Schwarz Information Criterion (SIC), values shows that the ANN-ABC is performing better than other MLE method for better estimation accuracy under the stated evaluation criteria.

5 Dataset

To calculate the viability of the offered estimation techniques in practice, we have examined the medical charts of 299 patients with heart failure who were hospitalized at the Faisalabad Institute of Cardiology and Allied Hospital (Punjab, Pakistan) at April-December 2015 [26]. There were 105 women and 194 men with the age range of 40 and 95 years (Table 1). Patients were all left ventricular systolic dysfunction and were already under prior heart failure, of which they are classified into NYHA class III or IV [29-31].

5.1 Homogeneity Testing for the Inverse Weibull Process

The Inverse Weibull Process (IWP) is classified as nonhomogeneous when its event rate varies with time t indicating time-dependent behavior. It becomes homogeneous if $\lambda = 0$, and it is nonhomogeneous when $\lambda \neq 0$. To assess this, the following hypothesis test is applied [17]:

$H_0: \lambda = 0$

$H_1: \lambda \neq 0$

which can be tested through the following statistics:

$$Z = \frac{\sum_{i=1}^{n}\tau_i - \frac{1}{2}n\tau_0}{\sqrt{\frac{n\tau_0{}^2}{6}}}, \quad (18)$$

where Z represent calculate test, $\sum_{i=1}^{n}\tau_i$ is the sum of the accident times for a period $(0, \tau_0]$, and n represents the number of accidents that occur in a period $(0, \tau_0]$.

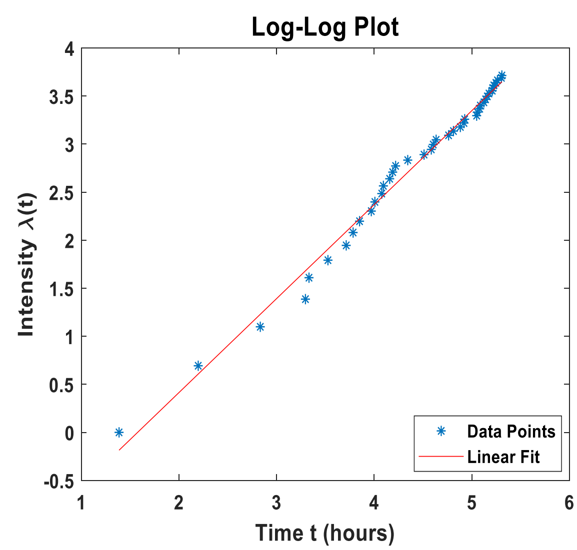

Fig. 1: Cumulative number of days of operation between two shutdowns with their occurrence times on a logarithmic scale.

The scatter plot shows evident linear tendency, which implies that the data is highly suitable to the modeling by means of the IWP function. Similar performance of the MLE and ANN-ABC especially in a sample size of 299 could be referred to as the strengths on which the two methodologies are based on. Both also attempt to reduce the gap between observed and predicted values, but they do so in different inferential structures MLE finds the value of the parameters that maximizes likelihood of the data given a set of (fixed) parameters. This agreement in the performance demonstrates the strength of the performance of the IWP model at moderate sample size.

Table 2. RMSE and BIC values for methods used to estimate the IWP parameters

Units	Size	Method	$\hat{\beta}$	$\hat{k}$	RMSE	BIC
DS1	105	MLE	0.31268	0.20157	26.948	24.726
		ANN-ABC	0.36394	0.25283	**22.906***	**20.716***
DS2	194	MLE	0.2248	0.1137	29.985	27.775
		ANN-ABC	0.3870	0.2761	**27.576***	**25.476***

Table 2 shows estimate of parameters of IWP computed from the proposed estimation schemes of this study. From the values of the RMSE and ANN-ABC model performed better as it provided more efficient estimators in describing the underlying structure in data.

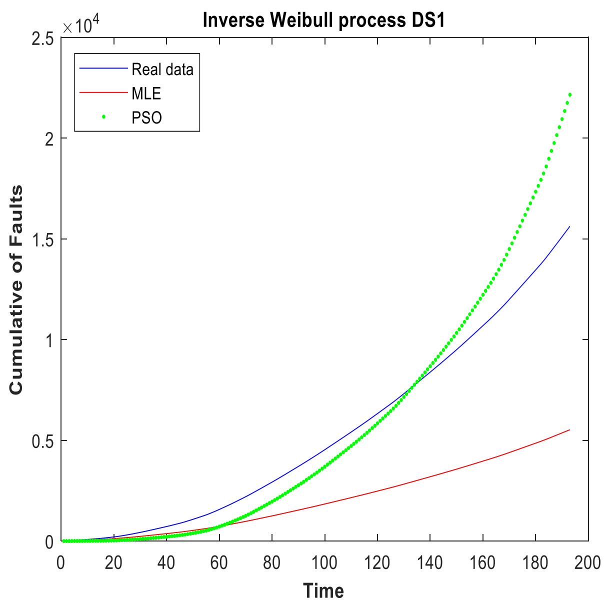

Fig. 2: Comparative Estimation of the Cumulative Failure Function for 194 Men Aged 40 and Above Using MLE and ANN-ABC Methods Under the Inverse Weibull Process Model (DS1).

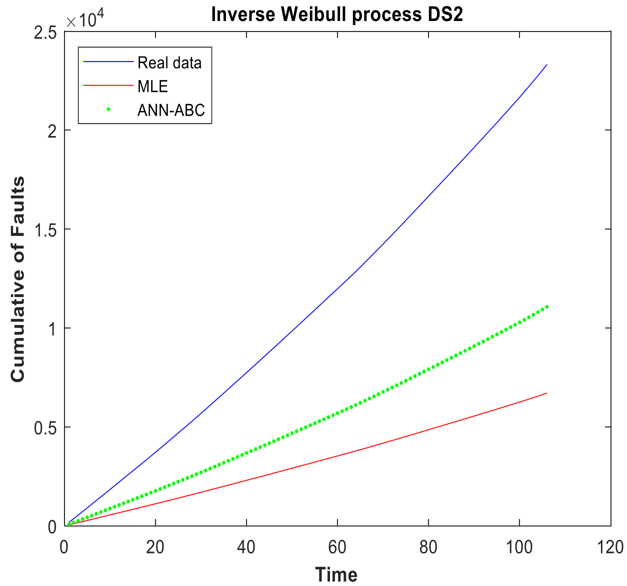

Fig. 3: Comparative Estimation of the Cumulative Failure Function for 105 women Aged 40 and Above Using MLE and ANN-ABC Methods Under the Inverse Weibull Process Model (DS2).

The estimates of cumulative failure functions of the male (n=194) and female (n=105) heart failure patients under the IWP model are demonstrated in both natural and ANN-ABC method shown in Figures 2 and 3 respectively. In both instances the ANN-ABC model fits better to the actual cumulative failure data, especially in the case of early and mid-life failures. MLE also has a similar trend to the general trajectory, but the deviation remains at a little bit higher point than in general, paying more attention to the period over time. These graphical results agree with the quantitative results in Table 2, where ANN-ABC cells showed smaller Bayesian Information Criterion (BIC) values, which represent an improvement in fit in the model, even though RMSE was only somewhat smaller in small samples. The graphs emphasize the stability of ANN-ABC in the estimation of failure intensity in non-homogenous settings especially real-world clinical data.

6 Conclusion and Future Work

A hybrid estimation of an Artificial Bee Colony (ABC) algorithm was compared as a possible combination with Artificial Neural Network (ANN) as an efficient framework to estimate the parameters in the Inverse Weibull Process (IWP) under a Non-Homogeneous Poisson Process (NHPP) distribution. Conducted with simulated as well as real world clinical failure data, the ANN-ABC method showed better accuracy when compared to the classical Maximum Likelihood Estimation (MLE) technique in terms of input data size; it is found to be more accurate with moderate to large samples. Its efficiency and robustness were supported by lower values of Root Mean Squared Error (RMSE) and Bayesian Information Criterion (BIC) and confirmed that it was able to capture time-dependent failure behavior. The results attest to the possibility of sophisticated algorithms in boosting reliability modeling of complex data-driven systems like predictive maintenance in cyber-physical systems, health informatics and IoT-based surveillance systems. The hybrid ANN-ABC model can be described as a scalable and adaptive mechanism of estimation that can be applied in real-world deployment without reliable performance of the traditional estimation approaches. The priority of future work will be to combine the Bayesian inference, imperfect repair modeling, and generalize it to the streaming or real-time data accommodating systems that are dynamic. Also, the next step in this project can be developing adversarial robustness and uncertainty quantification approaches to AI-driven reliability modeling supporting intelligent, secure, and trustworthy infrastructure.

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Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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