A Choice of Performance Metrics for Evaluating Predictive Accuracy of Survival Models

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Abstract: This research critically assessed the predictive accuracy of parametric survival models (Weibull, Exponential, Log-logistic, and Gompertz) against penalized Cox PH models (Ridge, Lasso, and Elastic Net) using both simulated data (sample sizes of 100, 200, and 1000) and real-world data from the Nigerian Demographic and Health Survey (NDHS). The findings showed that parametric models, particularly the Weibull and Log-logistic models, consistently outperformed the others, achieving the highest Concordance Index (C-index) and the lowest Mean Absolute Error (MAE) and Mean Squared Error (MSE), indicating superior discrimination and calibration. In contrast, penalized Cox models underperformed, especially with a larger number of covariates, and the Gompertz model exhibited poor predictive performance under all conditions. Notably, parametric models remained stable and consistent even with smaller sample sizes and high-dimensional, complex data. These results highlighted the reliability of parametric models in survival analysis, particularly in small-sample and high-dimensional settings, offering key insights to inform future infant and child health research.

Keywords: Survival analysis, Infant Mortality, Child Mortality, Predictive Performance, Penalized Cox Proportional Hazards, Performance Metrics.

1. INTRODUCTION

Survival analysis is a critical statistical technique for the modeling of time-to-event data, used extensively in healthcare, economics, and social sciences. Its ability to accommodate censored observations cases where the event of concern has not occurred by the completion of the study duration makes it a tool that cannot be avoided for the prediction of significant outcomes such as disease progression, patient survival, and system failure [1]. This ability enables researchers and policymakers to make informed decisions based on data, maximizing intervention approaches and resource allocation in various fields.

Survival models are generally categorized into parametric, semi-parametric, and non-parametric models, each with distinct analytical capabilities. Parametric models, including Weibull, Exponential, and Log-logistic, presume certain distributions for survival times, allowing for accurate time-to-event estimation. On the other hand, semi-parametric models such as the Cox Proportional Hazards (PH) model do estimate relative risk without assuming a baseline hazard function [2]. Non-parametric methods, such as the Kaplan-Meier estimator, have no assumptions made from observed data, providing adaptability but being predictive in low-complexity situations.

Measuring model performance is also necessary, as improper selection of the metric can misleadingly portray predictive ability. The Concordance Index (C-index), proposed by [3], is one of the most commonly applied measures of discrimination, and it takes values closer to 1 as the predictive ranking improves [4, 5]. The C-index can be less than perfect in reflecting accuracy when there are censored data [6,7]. Complementary measures such as Mean Absolute Error (MAE) and Mean Squared Error (MSE) offer direct measures of prediction error, with MAE offering resistance to outliers and MSE as a sensitive measure of precision [8, 9].

Existing research has emphasized the need for model-metric pairing. Research conducted by [10] showed that parametric models such as Weibull and Log-logistic are best in the representation of intricate hazard functions, which hold significance in child mortality studies. [11, 12] similarly established that parametric models tended to outperform the Cox model in instances of nonlinear survival trends ubiquitous in public health.

Due to the serious implications of survival analysis in high-risk fields such as medicine and public health, model choice and metric assessment are of utmost importance. This article systematically contrasts the prediction performance of parametric and penalized Cox models by using key metrics C-index, MAE, and MSE providing valuable advice for researchers and policymakers who deal with survival data, particularly in resource-poor settings and in infant and child mortality research.

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2. MATERIAL AND METHODS

2.1. Material

This study utilized the Nigerian Demographic and Health Survey (NDHS) dataset with 10,400 observations. The models applied include penalized Cox models (Lasso, Ridge, and Elastic Net) and parametric models (Weibull, Exponential, Log-Logistic, and Gompertz). Covariates such as sex of child, toilet facilities, size of family, place of residence, source of drinking water, birth order, preceding birth interval, mother's education, wealth index, access to health care, breastfeeding, maternal current age, and age at first birthwere incorporated based on exploratory analysis and literature review.

2.2. Model Fitting

A variety of survival models were applied to the dataset, including Penalized Cox Proportional Hazards, Weibull, Exponential, Gompertz, and Log-logistic models. The selection of these models was predicated on their theoretical foundations and relevance to an array of survival data types. The analysis of the data was conducted utilizing the "R" programming language for the purposes of model fitting and subsequent evaluation. The models employed in this investigation are delineated below;

2.2.1. Selection of Covariates and Penalization Constants

The covariates included in the model were selected based on a combination of prior literature and exploratory analysis. Specifically, variables such as child sex, sanitation facilities, household size, and socioeconomic status were identified as potential predictors of infant and child mortality. To optimize the performance of penalized Cox models, penalization constants (lambda) were chosen using cross-validation techniques. This process involved partitioning the dataset and evaluating different values of the regularization parameters to select the optimal lambda values for each model see [1, 9, 13].

2.2.2. Cox Proportional Hazards Model

The Cox Proportional Hazards (Cox PH) model is a popular statistical method used in survival analysis. It models the relationship between the survival times of subjects and one or more predictor.

$$h(t/X) = h_0(t)\exp(\beta^T X) \quad (2.1)$$

Where:

$h(t/X)$: is the hazard function at time t given covariates X.

$h_0(t)$: is the baseline hazard function.

β : is the vector of coefficients associated with the covariates.

2.2.3. Penalized Cox Models

Penalized Cox models extent the traditional Cox model by adding a penalty term to the likelihood function. This is particularly useful when dealing with high-dimensional data where the number of covariates exceeds the number of observations. The penalty term helps to prevent overfitting and improve model interpretability by shrinking towards zero. The three types of penalization are: Lasso (Least Absolute Shrinkage and Selection Operator)

Lasso Cox Model

The Lasso Coxmodel incorporates $L1$ penalty, which applies a constraint proportional to the absolute values of the regression coefficients. This approach encourages sparsity in the model by shrinking some coefficients to exactly zero, effectively performing variable selection. The mathematical formulation of the Lasso Cox model is given by:

$$\hat{\theta} = \arg\min(-\log L(\theta) + \psi \sum |\theta_j|) \quad (2.2)$$

Where:

ψ : is the tuning parameter that controls the strength of the penalty.

$\sum |\theta_j|$ represent the $L1$ penalty term.

Ridge Cox Model

The Ridge Cox model introduces the $L2$ penalty, which applies a constraint proportional to the squared values of the regression coefficients. Unlike the Lasso penalty, Ridge does not set any coefficients to zero but instead shrinks them towards zero, reducing model complexity and preventing overfitting. The Ridge Cox model is mathematically expressed as:

$$\hat{\theta} = \arg\min(-\log L(\theta) + \psi \sum |\theta_j^2|) \quad (2.3)$$

Where:

ψ : is the tuning parameter that controls the strength of the penalty.

$\sum \theta_j^2$: is the $L2$ penalty term.

Elastic Net Cox Model

Elastic Net Cox model is a hybrid approach that combines properties of both Lasso $L1$ and Ridge $L2$ properties. It is particularly useful in cases where predictors are highly correlated, as it encourages grouping effects where correlated variables are selected together. The Elastic net model can be expressed as:

$$\hat{\theta} = \arg\min(-\log L(\hat{\theta}) + \psi_1 \sum |\theta_j| + \psi_2 \sum \theta_j^2) \quad (2.4)$$

Where:

ψ_1, and ψ_2 are turning parameters for the $L1$, and $L2$ penalties, respectively.

The combination of the penalties balances sparsity (LASSO), and shrinkage (Ridge)*, leading to the more stable and interpretable model.

Weibull Model

The Weibull model is a parametric survival model that assumes a hazard function of the form;

$$h(t) = \psi\tau t^{\tau-1} \quad (2.5)$$

Where:

ψ, and τ are parameters. This form allows the hazard rate to increase, decrease, or remain constant over time, depending on the value of τ.

Exponential Model

The Exponential model is a special case of the Weibull model where the hazard rate is constant overtime, implying that the event risk does not change as the time progresses. The hazard function is given by;

$$h(t) = \theta \quad (2.6)$$

This model is particularly useful in scenarios where the assumption of a time-independent hazard rate is reasonable, offering a simple and interpretable survival analysis framework.

Log-logistics Model

The Log-logistic model is suitable for data exhibiting various hazard shapes, including increasing, decreasing, or bathub-shape hazard functions. It is a parametric model where the hazard function can be expressed as:

$$h(t) = \frac{\tau\theta t^{\tau-1}}{1-(\theta t^{\tau})} \quad (2.7)$$

Where:

θ : is the scale parameter

τ : is the shape parameter

Gompertz Model

The Gompertz model is commonly used to model hazard rates that increase exponentially over time, making it particularly applicable in aging and mortality. The hazard function is given by:

$$h(t) = \theta e^{\tau t} \quad (2.8)$$

Where:

θ : is the scale parameter

τ : is the shape parameter

2.3. Justification of the Evaluation Metrics

The selection of the Concordance Index (C-index), Mean Absolute Error (MAE), and Mean Squared Error (MSE) as the primary performance indicators is particularly relevant for this study, as these metrics provide comprehensive insight into the predictive accuracy and discriminative ability of survival models in the context of infant and child mortality.

2.3.1. C-index

The Concordance Index (C-index) is a widely used metric for evaluating the discriminative ability of survival models. It measures how well a model can rank survival times by comparing the predicted risk scores with actual outcomes. In survival analysis, the C-index is particularly useful because it handles censored data, which is common in time-to-event studies, such as when some individuals have not yet experienced the event by the end of the study [1].

The C-index value can be given by:

$$C = \frac{\sum I(r_i > r_j) I(t_i < t_j)}{\sum I(t_i < t_j)} \quad (2.9)$$

Where;

r_i, and r_i are the predicted risk scores for individual i and j

t_i, and t_j are the actual event

$I(t_i < t_j)$, is an indicator function that equals 1 if individual i has an earlier event time than individual j.

$I(r_i > r_j)$, is an indicator function that equals 1 if the model correctly predicts that individual j

The C-index ranges from 0.5 to 1

$c = 0.5$, indicates random prediction

$c = 1$, indicates perfect prediction

$c < 0.5$, indicates worse-than-random prediction.

2.2.2. Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) is a measure of the average magnitude of errors between the predicted and actual values. In survival analysis, MAE assesses how close the predicted survival times are to the observed survival times. Unlike the C-index, which evaluates ranking, MAE directly measures the accuracy of the predicted time-to-event outcomes, making it an important metric for evaluating the precision of parametric survival models.

Mathematically, the MAE is the mean of the absolute differences between the predicted survival times $\hat{T}_i$ and the observed survival times T_i, adjusted for censoring. The expression for MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|T_i - \hat{T}_i\right| \tag{2.9}$$

Where;

T_i : is the actual (observed) survival time for individual i

$\hat{T}_i$: is the predicted survival time for individual i

n : is the total number of individual

2.2.3. Mean Square Error (MSE)

MSE measures the average of the squares of the errors between observed and predicted survival time lower MSE values indicate better model performance. The calculation was performed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left|T_i - \hat{T}_i\right|^2 \tag{2.10}$$

Where:

T_i : is the observed survival time

$\hat{T}_i$: is the predicted survival time

n : is the number of the observations

3. RESULTS

We presented the performance of the penalized Cox models (Lasso, Ridge, Elastic Net, and Adaptive Lasso) and parametric models (Weibull, Exponential, Log-Logistic, and Gompertz) using three key performance metrics; Concordance Index (C-index), Mean Absolute Error (MAE), and Mean Squared Error (MSE). Simulation experiment were conducted with different sample sizes (100, 200, and 1000) with correlation value $\rho = 0.6$ to assessed the models' robustness. Table **1a**, **1b**, and **1c** summarized each model's predictive performance across these sample size levels.

4. DISCUSSION

Simulation outcomes at different sample sizes (100, 200, and 1000) all pointed to the superior performance of parametric models, especially Weibull and Log-logistic, in forecasting infant and child mortality. The models all had the highest C-index values and the lowest MAE and MSE scores, affirming their strength for survival analysis. The Log-logistic model, in particular, had the lowest MAE, which is a measure of outstanding accuracy in forecasting actual survival times.

Table **1a** showed the simulation results with smaller sample sizes (n = 100), illustrating that parametric models (Weibull, Exponential, and Log-logistic) performed better than penalized Cox models (Ridge, Lasso, and Elastic Net) in terms of predictive accuracy. The maximum C-index values (0.8087 and 0.8089 for Weibull and Log-logistic, respectively) reflected better discriminatory ability. These models also had the lowest MAE and MSE values, improved calibration, and smaller prediction errors. Conversely, the Gompertz model produced a C-index of about 0.5, indicating poor discrimination in prediction. Penalized Cox models demonstrated C-index rates of about 0.191, with deteriorating performance with increasing numbers of variables, indicating possible overfitting and reduced ability to model intricate survival trends in small samples.

Table **1b** presented estimates for a sample size of (n = 200), where performance disparity between parametric and penalized Cox models continued. Weibull and Log-logistic models resulted in good C-index values (~0.8089) along with comparatively smaller MAE and MSE, establishing their trustworthiness for small-to-medium sized datasets. Exponential was next in line with a comparatively reduced performance but yet competitive. At the same time, the Cox regularized models had marginally better C-indices (~0.191) but increasing MAE and MSE with more features, proving them to be susceptible to high-dimensional data despite regularizing. The Gompertz model still performed the worst, confirming its inappropriateness for the provided survival data.

For bigger sample sizes (n = 1000) in Table **1c**, parametric models were still superior but their performance deteriorated with increasing variable numbers. C-index of the Weibull model decreased to 0.8042 when p = 3 and 0.8017 when p = 9, while MAE and MSE values increased, showing decreasing efficiency in larger dimensional spaces. Penalized Cox models improved somewhat, with stabilized C-indices

Table 1a: Simulated Predictive Performance of Survival Models for Sample Size n = 100 with $\rho = 0.6$

Model	Number of Covariates (p)	C-index	MAE	MSE
Ridge	3	0.1913	2.5123	14.6210
	6	0.1914	2.8147	15.7642
	9	0.1915	3.0128	16.8791
Lasso	3	0.1911	2.6153	15.1254
	6	0.1912	2.9121	16.2035
	9	0.1913	3.1245	17.4123
Elastic Net	3	0.1912	2.6547	15.3421
	6	0.1913	2.9451	16.4127
	9	0.1914	3.1592	17.6138
Weibull	3	0.8087	0.9547	3.0165
	6	0.8075	1.1021	3.5241
	9	0.8052	1.3412	4.5210
Exponential	3	0.8086	0.9946	3.6883
	6	0.8069	1.1457	4.2145
	9	0.8045	1.3854	5.1987
Gompertz	3	0.5000	1.6351	5.8615
	6	0.4989	1.8125	6.9124
	9	0.4963	2.1121	8.5412
Log-logistic	3	0.8089	0.7851	1.9268
	6	0.8078	0.9451	2.3542
	9	0.8054	1.1982	3.1423

Table 1b: Simulated Predictive Performance of Survival Models for Sample Size n = 200 with $\rho = 0.6$

Model	Number of Covariates (p)	C-index	MAE	MSE
Ridge	3	0.1915	2.9152	15.8698
	6	0.1917	3.0193	16.7412
	9	0.1919	3.2101	17.9825
Lasso	3	0.1912	3.0224	16.9410
	6	0.1913	3.1842	17.8923
	9	0.1915	3.3812	19.2101
Elastic Net	3	0.1913	3.0243	16.9523
	6	0.1914	3.2413	18.0142
	9	0.1916	3.4517	19.3251
Weibull	3	0.8087	0.9547	3.0165
	6	0.8072	1.1023	3.5287
	9	0.8049	1.3421	4.5128
Exponential	3	0.8086	0.9946	3.6883
	6	0.8067	1.1487	4.2011
	9	0.8041	1.3892	5.1965
Gompertz	3	0.5000	1.6351	5.8615

(Table 1b). Continue

Model	Number of Covariates (p)	C-index	MAE	MSE
	6	0.4987	1.8197	6.9874
	9	0.4962	2.1128	8.5421
Log-logistic	3	0.8089	0.7851	1.9268
	6	0.8075	0.9482	2.3515
	9	0.8048	1.1987	3.1479

Table 1c: Simulated Predictive Performance of Survival Models for Sample Size n = 1000 with $\rho = 0.6$

Model	Number of Covariates (p)	C-index	MAE	MSE
Ridge	3	0.1921	3.4119	19.8723
	6	0.1923	3.5121	20.3415
	9	0.1925	3.7015	21.5212
Lasso	3	0.1916	3.5186	20.6732
	6	0.1917	3.6234	21.3142
	9	0.1919	3.8217	22.5413
Elastic Net	3	0.1918	3.5315	20.7328
	6	0.1919	3.6451	21.4512
	9	0.1921	3.8457	22.7210
Weibull	3	0.8042	1.3421	4.5128
	6	0.8032	1.4517	4.9121
	9	0.8017	1.6123	5.4513
Exponential	3	0.8035	1.3892	5.1965
	6	0.8024	1.5231	5.7214
	9	0.8009	1.7123	6.3142
Gompertz	3	0.4961	2.1128	8.5421
	6	0.4945	2.3145	9.3412
	9	0.4927	2.6123	10.5123
Log-logistic	3	0.8048	1.1987	3.1479
	6	0.8037	1.3142	3.5121
	9	0.8021	1.5123	4.0132

at 0.192, although their MAE and MSE grew rapidly with additional variables, indicating continued issues with dimensionality in spite of penalization. The Gompertz model continued to be the poorest, reinforcing its unsuitability for survival analysis in this scenario.

Application to real infant and child mortality data from the Nigerian Demographic and Health Survey (NDHS) supported these results. Table **2** displayed the predictive ability for infant death, with parametric models besting penalized Cox models for a second time. The best C-index results were seen from the Log-logistic and Weibull models (0.7892 and 0.7890, respectively), showing superior discriminatory strength. Penalized Cox models on the other hand had much smaller C-index (~0.21) and a much higher MAE and MSE score, depicting poorer predictive performance. The Gompertz model was the worst-performing one, with a C-index of 0.5000, effectively making random predictions.

The parametric models' performance showed that the Weibull model was the best infant mortality predictor, with the lowest MAE (0.6191) and MSE (0.6861). The Log-logistic model took second place,

Table 2: Real World Data of Infant Mortality with Dataset (n=10,400)

Model	C-index	MAE	MSE
Ridge	0.2115	1.8992	5.5705
Lasso	0.2111	1.8879	5.5136
Elastic Net	0.2111	1.8863	5.5051
Weibull	0.7890	0.6191	0.6861
Exponential	0.7871	0.6907	0.7424
Gompertz	0.5000	2.0271	5.1974
Log-logistic	0.7892	0.6030	0.7068

Table 3: Real World Data of Child Mortality with Dataset (n=10,400)

Model	C-Index	MAE	MSE
Ridge	0.2310	21.7415	726.8875
Lasso	0.2303	21.5982	722.1553
Elastic Net	0.2303	21.6042	722.3374
Weibull	0.7706	7.7191	99.1494
Exponential	0.7703	8.0855	103.3872
Gompertz	0.5000	22.4847	737.3196
Log-logistic	0.7706	7.6616	101.8146

with lower MAE (0.6030) but marginally higher MSE (0.7068). The Exponential model was reasonably good (C-index: 0.7871) but had higher MAE (0.6907) and MSE (0.7424). On the other hand, the penalized Cox models achieved significantly higher MAE and MSE (MAE: 1.8863-1.8992, MSE: 5.5051-5.5705) values, highlighting their worse fit to the dataset.

Table **3** highlighted predictive performance in child mortality, further testifying to the excellence of parametric models. The Weibull and Log-logistic models achieved the highest C-index values (~0.7706) with the lowest MAE and MSE scores, affirming their predictive accuracy in time-to-event outcomes. The Log-logistic model possessed the lowest MAE (7.6616) and an MSE of 101.8146, whereas the Weibull model had the lowest MSE (99.1494), which reflected the most accurate mortality forecasts. In contrast, non-penalizedCox models possessed significantly lower C-index values (~0.23) and considerably higher MAE and MSE scores. The Gompertz model continued to be the poorest with the C-index being 0.5000, having the largest MAE (22.4847), and the largest MSE (737.3196), which only asserted its inability to generate useful risk classification.

All these results conformed with past research work [14-16], confirming the reliability and accuracy of parametric models in survival analysis across sample sizes. Conversely, penalized Cox models performed poorly for smaller samples and high-dimensional data, for which overfitting continued even after penalization. As the covariate number rose, their C-index flattened (~0.19–0.23), whereas error measures degraded, indicating that standard penalization could be inadequate for overcoming the curse of dimensionality.

Future studies might investigate more sophisticated penalized methods, like Adaptive Lasso or Group Lasso, that accommodate grouped covariate structures and could improve model stability in high-dimensional contexts [16]. These findings suggest that parametric models (Weibull and Log-logistic) are particularly advantageous for public health research in low-resource settings. Their higher predictive accuracy can guide health interventions, helping policymakers allocate resources more efficiently. For example, identifying high-risk groups through more accurate time-to-event predictions enables targeted maternal and child health programs, reducing mortality rates in vulnerable populations

5. CONCLUSION

This study demonstrated that parametric survival models, particularly Weibull and Log-logistic, offered superior predictive accuracy in infant and child mortality analysis. These models consistently outperformed penalized Cox models in discrimination and calibration, making them more suitable for survival estimation, especially in resource-limited settings. The findings emphasized the importance of selecting appropriate survival models based on data structure. When a well-defined hazard function was evident, parametric models were prioritized. Penalized Cox models remained useful for high-dimensional data but required careful regularization to mitigate performance loss. In scenarios where hazard assumptions were unclear, hybrid approaches integrating parametric models with machine learning techniques enhanced predictive reliability. These insights provided valuable guidance for researchers and policymakers aiming to optimize survival modeling in public health applications.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Ethics approval was not required for this research work, as it did not involve direct interaction with human or animal subjects.

CONSENT FOR PUBLICATION

The dataset used in this study is publicly available, and informed consent was obtained by the original data collectors as part of the Nigerian Demographic and Health Survey (NDHS) protocol.

AVAILABILITY OF DATA AND MATERIALS

The datasets used during the current study are easily accessible from: https://dhsprogram.com/data/dataset/Nigeria_Standard DHS_2018.cfm?flag=1

COMPETING INTERESTS

The authors declare that they have no competing interests.

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AUTHOR CONTRIBUTIONS

All authors contributed equally to the conception, design, analysis, and writing of the manuscript.

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