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# FORECASTING SURRENDERS IN PERIODIC SAVINGS INSURANCE PRODUCTS: A COMPARATIVE ANALYSIS OF ARIMA, ETS, AND PROPHET MODELS

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## ABSTRACT

This study provides an empirical comparison of ARIMA, ETS, and Prophet forecasting models for predicting monthly surrender volumes in periodic savings insurance products using aggregated data from Tunisian insurance companies (2016-2024).

Using a rigorous train-test protocol with data split at 2022/2023, we assess model performance via Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Results demonstrate that ARIMA(0,1,1) and ETS(A,N,N) deliver superior and essentially equivalent performance (MAE: ~366, RMSE: ~447, MAPE: ~34.6%), substantially outperforming Prophet (MAE: 403.77, RMSE: 494.92, MAPE: 37.56%).

The findings underscore the importance of model-data alignment: traditional parsimonious approaches excel for non-seasonal insurance time series, while sophisticated decomposition methods designed for pronounced seasonality prove ineffective for this application.

We identify practical implications for liquidity risk management, reserve adequacy, and actuarial forecasting in emerging market contexts.

**KEYWORDS:** Life insurance; Surrenders; Time series forecasting; ARIMA; ETS; Prophet.

## 1. INTRODUCTION

Periodic savings insurance products represent a cornerstone of life insurance portfolios in developing markets.

These products combine systematic accumulation with insurance protection, but embed surrender options that create significant cash flow and liquidity challenges for insurers. Unexpected surrender surges can force asset liquidation under adverse market conditions, crystallizing losses and disrupting Asset-Liability Management strategies.

Accurate surrender forecasting therefore constitutes a critical component of enterprise risk management for insurance companies, directly affecting capital adequacy, solvency, and profitability.

The actuarial and statistical literature offers diverse methodological approaches. Traditional Box-Jenkins ARIMA models excel at capturing linear temporal dependencies, exponential smoothing (ETS) provides adaptive filtering of non-seasonal trends, while Prophet was designed specifically for series exhibiting strong seasonality and structural breaks characteristics often absent in insurance surrender data.

Determining which method performs optimally for this application requires rigorous empirical comparison.

## 2. Research Objectives

This paper conducts a systematic empirical comparison of ARIMA, ETS, and Prophet forecasting methodologies applied to aggregate monthly surrender data from Tunisian insurance companies.

We evaluate forecasting accuracy using multiple complementary metrics and provide practical guidance for model selection in insurance surrender prediction. Our contribution addresses the limited empirical literature on actuarial forecasting in emerging market contexts.

## 2. Literature Review

Surrender behavior in life insurance is driven by both rational financial considerations and behavioral factors. Kim (2005) established that interest rate differentials between policy crediting rates and market alternatives significantly influence surrender propensity, while Kuo et al. (2004) demonstrated that unemployment rates proxy for policyholder liquidity needs.

These findings motivate investigation of deterministic economic drivers beyond pure time series patterns.

From a methodological perspective, the literature identifies distinct advantages and limitations of competing approaches.

Box and Jenkins (1970) developed ARIMA models that capture linear autocorrelation structures through parsimonious specifications. Hyndman et al. (2008) formalized exponential smoothing within a state space framework, enabling flexible decomposition of time series into level, trend, and seasonal components. Taylor and Letham (2018) introduced Prophet to accommodate multiple seasonal patterns and trend changepoints features valuable for retail and web traffic data but potentially disadvantageous when applied to series lacking such patterns.

Comparative studies reveal context-dependent performance. Siami-Namini and Namin (2018) found that ARIMA maintains competitive performance for shorter horizons and smaller datasets, while deep learning approaches dominate with extended horizons and large training samples. Peovski and Ivanovski (2024) documented that SARIMA and ETS achieved comparable accuracy for non-life insurance premiums.

These findings underscore the importance of empirical model evaluation tailored to specific applications rather than assuming universal superiority of any methodology.

## 3. Data and Method

Our analysis employs aggregated and anonymized monthly surrender data from Tunisian insurance companies spanning January 2016 through December 2024 (108 observations). The dataset represents aggregate surrender counts across participating insurers for periodic savings products, with monthly frequency aligning with standard actuarial reporting cycles.

The time series exhibits a generally upward trend from ~600 surrenders in 2016 to ~1,600 in 2024, with elevated volatility during 2023-2024.

Visual inspection reveals weak seasonal patterns, consistent with the absence of pronounced intra-year cyclicality in surrender behavior for this market.

We implement a fixed-origin train-test evaluation protocol: training data encompasses 84 monthly observations (2016-2022) used for model estimation and parameter calibration; testing data comprises 24 monthly observations (2023-2024) reserved exclusively for out-of-sample forecast evaluation. This 78%-22% split provides sufficient historical data for reliable parameter estimation while maintaining an adequate forecast horizon for meaningful accuracy assessment.

## 4. Models

### 4.1 ARIMA

General ARIMA(p, d, q) form:

$\varphi(L)(1 - L)^{d}\, y_t = \theta(L)\, \varepsilon_t$

Expanded equations:

Autoregressive part (AR): $y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots + \varphi_p y_{t-p} + \dots$

Differencing part (I): $(1 - L)^{d}\, y_t$ removes trend / nonstationarity

Moving-average part (MA): $\varepsilon_t = \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \dots$

- Variable definitions:
- $y_t$ : Observed time-series value at time t
- $\varphi_1 \dots \varphi_p$ : Autoregressive coefficients
- $\theta_1 \dots \theta_q$ : Moving-average coefficients
- d : Order of differencing
- $\varepsilon_t$ : Error term ($\varepsilon_t \sim N(0, \sigma^2)$)
- L : Lag operator ($L\, y_t = y_{t-1}$)
- p : AR order, q : MA order
- $\sigma^2$ : Variance of the error term

### 4.2 ETS(A,N,N) – Simple Exponential Smoothing

Measurement equation:

$y_t = \ell_{t-1} + \varepsilon_t$

State equation:

$\ell_t = \ell_{t-1} + \alpha\varepsilon_t$

Error term:

$\varepsilon_t \sim N(0, \sigma^2)$

Forecast equation:

$\hat{y}_{t+h|t} = \ell_t$

- Variable definitions:
- $y_t$ : Observed value at time t
- $\ell_t$ : Level (smoothed estimate) at time t
- $b_t$ : Trend component at time t
- $\alpha$ : Smoothing parameter for level ($0 \leq \alpha \leq 1$)
- $\beta$ : Smoothing parameter for trend ($0 \leq \beta \leq 1$)

- $\varepsilon_t$ : Error term ($\varepsilon_t \sim N(0, \sigma^2)$)
- $\sigma^2$ : Variance of the error term
- $\hat{y}_{t+h|t}$ : Forecast h periods ahead
- h : Forecast horizon

**4.3 Prophet**

Prophet decomposes a time series into trend, seasonality, and holiday/special effects components.

Model equation:

$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$

Where:

- g(t) : Trend component (piecewise linear or logistic growth)
- s(t) : Seasonality component (can include multiple seasonalities)
- h(t) : Holiday or special-event effects
- $\varepsilon_t$ : Error term / noise ($\varepsilon_t \sim N(0, \sigma^2)$)
- t : Continuous time index (day, month, etc.)

**5. Accuracy Metrics**

We report Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

$\text{MAE} = (1/n)\ \Sigma\ |yt - \hat{y}t|$

$\text{RMSE} = \sqrt{[(1/n)\ \Sigma\ (yt - \hat{y}t)^2]}$

$\text{MAPE} = 100 \times (1/n)\ \Sigma\ |(yt - \hat{y}t) / yt|$

**6. RESULTS**

**Table 1. Out-of-sample forecast accuracy metrics (24-month test period, 2023-2024). MAE and RMSE in absolute count units; MAPE in percentage.**

Out-of-sample forecast accuracy (test period: 2023–2024):

| Model | MAE | RMSE | MAPE |
|---|---|---|---|
| **ARIMA(0,1,1)** | 365.28 | 445.89 | 34.60% |
| **ETS(A,N,N)** | 367.05 | 448.26 | 34.68% |
| **Prophet** | 403.77 | 494.92 | 37.56% |

ARIMA and ETS demonstrate superior and essentially identical performance, with ARIMA marginally optimal. The MAE of 365.28 surrenders represents forecast errors averaging

±31% of mean test period surrender volume (1,165 surrenders), indicating substantial but manageable prediction uncertainty. ETS achieves virtually identical results (MAE 367.05, 0.48% difference from ARIMA), reflecting their mathematical equivalence for this application.

Prophet exhibits substantially weaker performance with 10.5% higher MAE and 11.0% higher RMSE.

Analysis of forecast trajectories reveals systematic under-prediction during early test periods (2023), with Prophet's trend extrapolation failing to anticipate acceleration in surrender activity. This underperformance reflects Prophet's design priority: handling pronounced seasonality and well-defined changepoints, features absent in this time series.

## 7. DISCUSSION AND PRACTICAL IMPLICATIONS

### 7.1 DISCUSSION

Our findings validate established principles of time series model selection. ARIMA and ETS success reflects their alignment with observed data characteristics: non-stationary behavior addressable through first differencing, moderate autocorrelation requiring moving average or adaptive filtering, and absence of strong seasonality precluding benefit from seasonal decomposition.

These results parallel Box-Jenkins methodology's foundational principle: employ the simplest model adequate to capture temporal dependencies.

The near-identical ARIMA and ETS performance confirms their mathematical equivalence for this application. Both approaches implement essentially the same underlying model exponential smoothing of differenced data differing primarily in computational implementation.

The marginal ARIMA advantage likely reflects direct integration of differencing within model structure rather than applying exponential smoothing post-hoc.

Prophet's weaker performance provides instructive insights regarding model-data alignment. Designed for retail sales, web traffic, and similar business time series exhibiting strong multiple seasonalities and abrupt trend shifts, Prophet's sophisticated mechanisms prove counterproductive when applied to surrender data characterized by weak seasonality and gradually evolving trends.

The proliferation of parametrically independent seasonal components and changepoint flexibility may induce overfitting on limited training data, degrading out-of-sample prediction.

This finding reinforces that forecasting model selection cannot proceed from generic superiority claims but must account for specific data characteristics.

### 7.2 Practical Implications

For insurance practitioners, these results validate parsimonious ARIMA or ETS specifications as reliable forecasting tools for surrender prediction.

The forecast accuracy achieved with MAPE around 34.6% substantially exceeds naive benchmarks but remains subject to substantial uncertainty.

Practitioners should employ these forecasts as central tendencies requiring wide confidence intervals and supplemented by scenario analysis and stress testing rather than point predictions.

The 24-month forecast horizon examined here represents a relatively short planning window; accuracy would likely deteriorate further for longer-term strategic projections. The structural shift evident between training and test periods with 2023-2024 exhibiting substantially elevated surrender activity relative to 2016-2022 levels highlights critical challenges.

Pure time series models conditioned on historical data struggle to anticipate departures from historical patterns.

This limitation motivates future incorporation of economic covariates (interest rate differentials, unemployment, inflation) through ARIMAX specifications that explicitly model surrender drivers. However, such enhancements require reliable forecasts for exogenous variables themselves, introducing additional uncertainty.

## 8. LIMITATIONS AND FUTURE WORK

This study operates within several important constraints.

First, univariate time series models exclude economic and market information demonstrably important for surrender behavior. Future research should develop ARIMAX specifications incorporating interest rate spreads, unemployment, inflation, and consumer confidence indices to leverage available macroeconomic information.

Second, the relatively short time series (108 observations) and single-market focus limit generalizability. Extended data spanning multiple economic cycles and multiple jurisdictions would enhance robustness of conclusions.

Third, aggregate modeling obscures heterogeneity across policyholder cohorts, products, and distribution channels. Disaggregated microeconometric models could identify segment-specific surrender drivers enabling targeted retention initiatives.

Fourth, this analysis prioritizes point forecast accuracy without evaluating prediction interval calibration or probabilistic forecasting performance dimensions critical for risk management applications. Fifth, the study examines a specific historical period; model performance may vary across different economic regimes or market conditions.

Future research should:

(1) develop ARIMAX models incorporating macroeconomic variables;
(2) apply machine learning methods (gradient boosting, LSTM) potentially capturing nonlinear relationships;
(3) implement hybrid approaches combining statistical and machine learning methodologies;
(4) evaluate models across multiple markets and extended time periods;
(5) integrate aggregate time series forecasts with individual-level survival models;
(6) implement Bayesian approaches enabling continuous model updating as new data emerges.

## 9. CONCLUSION

This empirical comparison of ARIMA, ETS, and Prophet forecasting models for insurance surrender prediction documents that parsimonious traditional statistical approaches substantially outperform modern algorithmic alternatives when applied to this non-seasonal insurance time series. ARIMA(0,1,1) and ETS(A,N,N) deliver essentially equivalent performance (MAE ~366, RMSE ~447, MAPE ~34.6%), while Prophet exhibits substantially weaker accuracy (MAE 403.77, RMSE 494.92, MAPE 37.56%). These findings reinforce fundamental principles of statistical model selection: complexity must be justified by data characteristics, and methods designed for specific patterns (like Prophet's seasonal decomposition) prove ineffective when those patterns are absent.

For actuarial practitioners, the research provides practical guidance for model selection while acknowledging inherent forecast uncertainty.

While substantial prediction errors remain unavoidable, appropriate model selection yields meaningful improvements over alternatives.

As the Tunisian insurance market continues developing, robust forecasting capabilities become increasingly critical for effective risk management and sustainable operations. The methodological framework and empirical findings presented establish a foundation for continued research advancing insurance forecasting methodologies in emerging market contexts.

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