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Improving the prediction accuracy of a model using SVR with genetic algorithm

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Abstract:

The enhancement of predictive accuracy of the first-order integer autoregressive (INAR 1) model is the focus of the study through the effective amalgam of machine learning techniques and classical statistics. INAR (1) model structures are key elements for the prediction of nonnegative integer-valued time series processes. Conventional estimation methods include Classical Least Squares (CLS), Conditional Maximum Likelihood (CML), and Yule-Walker (YW) as compared with advanced methods like Support Vector Regression (SVR) and Genetic Algorithms (GA). A new clustering algorithm was created (with SVR to GA) to determine optimal INAR (1) model parameters. Computer simulation studies confirmed the effectiveness of the INAR-SVR and INAR-SVR-GA models compared to traditional methods.

The hybrid SVR-GA approach improved predictive accuracy by a wide margin, particularly with higher parameter values. This highlighted the robust performance of the SVR-GA-CML model, exhibiting uniform lending credibility at more diverse sample sizes and parameters. Integration of artificial intelligence into traditional statistical techniques in time series forecasting has taken the superior place. Enhancing accuracy is being turned into practical areas where forecasting economics and population studies need to make decision-making and allocation decisions with precise forecasts.

The originality of this study lies in the integration of statistical and AI hybrid techniques to upgrade the accuracy of time series forecasting. It provides the much-needed insight into the analysis of integer-valued time series and underscoring AI's transformational role in predictive analytics. Approval based on ethical standards was passed, and none of the contributors declared a conflict of interest.

Keywords: INAR (1) model, Support Vector Regression, Genetic Algorithms, forecasting, time series, artificial intelligence, parameter estimation.

1. Introduction:

Integer time series models, particularly the integer autoregressive first order (INAR (1)) model, are essential for forecasting events that occur as non-negative integers over time. The INAR (1) model was first introduced by (MacKenzie., 1985) and later refined by Al-Zaid and Al-Osh (1987). These models are widely applied in various domains, such as economic forecasting, population studies, and accident data analysis, where the integer nature of the data reflects real-world events.

While classical time series models like ARMA are effective for real-valued data, they struggle to handle integer-valued data due to their inability to preserve integer constraints. The binomial thinning procedure, introduced by (Steutel and Van Harn.,1979), addresses this issue, offering a robust modelling framework for countable data while retaining the desirable properties of ARMA models. The accuracy of parameter estimation in INAR (1) models is crucial for achieving reliable predictions. Traditional methods such as conditional least squares (CLS), conditional maximum likelihood (CML), and the Yule-Walker (YW) technique have been commonly employed for this purpose. However, there is still room for improvement, particularly in enhancing prediction accuracy. With advancements in machine learning, techniques like support vector regression (SVR) have demonstrated their potential to boost prediction performance. Furthermore, optimization algorithms such as genetic algorithms (GA) have been successfully employed to refine function approximation in SVR models. This combination of classical modelling approaches with machine learning methods provides a promising hybrid framework.

This study aims to estimate the parameters of the INAR (1) model using CLS, CML, and YW methods and subsequently enhance predictions through SVR with parameter optimization via genetic algorithms (GA). The remainder of the paper is structured as follows: Section 2 reviews related literature, Section 3 outlines the methodology used in the experimental analysis, Section 4 discusses the results, and Section 5 presents the study's conclusions and offers suggestions for future research (Mohammed, 2019; Juma & Al-Mohana, 2019; Wassan, 2023).

1.1 Literature review

(Bourguignon et al., 2019) developed two extended first-order integer autoregressive process models with Poisson innovations (INARDP and INARGP) to classify integer time series under conditions of equal variance, hypervariance, and excess variance. The study found that the conditional maximum likelihood (CML) method outperformed others in the INARDP (1) model for bias and mean square error (MSE). For the INARGP (1) model, CML performed best under excess variance, while the conditional least squares (CLS) method was optimal under hypervariance.

(Mohammed, 2019) introduced a new hybrid model, AR-Holt (5), along with a novel approach for estimating its parameters. The model's performance was compared with other traditional methods such as Yule-Walker, Burg, RA, LS, and LMS, using the MSE criterion. Simulations were conducted with different sample sizes (n = 150, 30, 70) and various parameter values (p = 0, 0.05, 0.10). The hybrid model was also applied to real barley crop data in Iraq. Results demonstrated that the proposed AR-Holt model produced superior parameter estimates compared to other models.

(Aradhye et al., 2019) employed a hybrid ARIMA-SVM model to decompose time series data into linear and nonlinear components using a moving average filter. This approach was applied to real data sets, including consumer price index (CPI) for inflation and crude oil production in India. The models were evaluated using MSE and MAE, showing that the hybrid ARIMA-SVM model consistently outperformed standalone ARIMA and SVM models.

(Sabah & Jasim, 2019) utilized the nonlinear regression BoxBod model to estimate the parameters using methods such as nonlinear least squares, maximum likelihood, and genetic algorithms. The latter used sum-of-squares and likelihood functions. The research, based on five simulation models, concluded that nonlinear least squares achieved the best results, while the genetic algorithm showed superior performance when the likelihood function was employed. (Wang, 2019) proposed a new INAR (2) model with a random coefficient and applied it to real-world data on stock trading volumes. Using a two-stage conditional least squares estimation method, the study compared the INAR (2) model to the classical AR (2) model through simulations. The findings indicated that the INAR (2) model with random coefficients provided more accurate estimates than the classical AR (2) model. (Xian et al., 2020) applied a hybrid EMD-SVR model to forecast crude oil prices using empirical mode decomposition (EMD) technology. The methodology decomposed time series data into intrinsic mode functions (IMFs) using Hilbert-Huang transform (HHT). The model was evaluated using RMSE, MAPE, and MAE on WTI crude oil price data, with results showing that the EMD-SVR hybrid model outperformed individual models. (Saha et al., 2021) explored a deep learning approach for stock price prediction using hybrid ARIMA-SVM and ARIMA-GRU models. The study applied these methods to data from the National Stock Exchange of India, comprising 2,511 samples. The ARIMA-GRU model outperformed ARIMA-SVM in long-term prediction accuracy. (YiChen, 2020) proposed a hybrid SVR-ARIMA model for forecasting municipal solid waste generation in China over six years. The study incorporated three data categories: urban population, annual urban expenditure, and GDP, and compared the models using MSE and MAPE. The SVR-ARIMA model delivered better results than standalone SVR or BPN models. (Lee & Lee, 2021) implemented the SVR method alongside the Tow TSVR algorithm, optimized using the particle swarm optimization (PSO) algorithm, for parameter estimation in linear and nonlinear INGARCH models. Simulations and predictive analysis using CUSUM tests showed that the Tow TSVR method provided superior predictive accuracy compared to machine learning and conditional averaging methods. (Belinda & Novita, 2021) analyzed the INAR(p) and AR(p) models using real data on prison populations in Nganjuk from April 2013 to July 2016. The INAR model was shown to effectively handle overly dispersed data, including infectious disease and robbery cases. Results demonstrated that the INAR (2) model outperformed the AR (2) model for predicting prison overcrowding issues, evaluated using AIC, BIC, and AICc criteria. (Ali & Mohammed, 2023) introduced a hybrid ARIMA-LSTM model to enhance prediction capabilities. The study compared multiple models (ARIMA, SVR, LSTM, LS-SVR, ARIMA-SVR, ARIMA-LSTM) using metrics like MSE, RMSE, MAE, and NSE. Results highlighted that ARIMA-LSTM achieved the best performance, particularly for drought prediction. (Rubio & Alba, 2022) employed a hybrid ARIMA-SVR model to forecast daily and cumulative returns of Colombian companies. Evaluations using MAPE, MAD, and MSD revealed that the hybrid model outperformed standalone discrete models in prediction accuracy. (Kachour et al., 2023) introduced the EP-RBINAR (1) model, which was estimated using CLS, CML, and Yule-Walker methods. Results indicated that the CML method provided the most effective parameter estimates, even with small datasets, achieving the lowest standard deviation among methods.

2. Materials and Methods:

2.1 First-Order Integer Autoregression (INAR (1))

The INAR (1) model (first-order integer autoregression) was introduced by McKenzie (1985) and further developed by Alzaid and Al-Osh (1987) to model and generate sequences of dependent count data (Bisaglia & Gerolimetto, 2018). The mathematical formulation of the INAR(1) model is follows:

$$X_t = \alpha \circ X_{t-1} + \varepsilon_t \cdots (1)$$

In this context, the parameter α is constrained to the interval [0,1], $\circ$ denotes the binomial thinning operation (Jazi&Alamatsaz, 2012). The term ε_t, referred to as the innovation, represents a sequence of independent and identically distributed random variables. Alzaid and Al-Osh (1987) demonstrated that the distribution of the model in Equation (1) can be expressed as: (I. Silva & Silva, 2006; Bartolo Guerrero, 2018).

$$X_t \overset{d}{=} \sum_{j=0}^{\infty} \alpha_i * e_{t-j} \; \ldots (2)$$

2.2 Conditional Least Squares (CLS)

The conditional least squares (CLS) method estimates the parameters by minimizing the sum of the squared differences between X_t and the conditional expectation of X_{t-1}, as defined by the following formula (I. Silva & Silva, 2006; Simarmata et al., 2017).

$$\mathbb{Q}_n(\theta) = \sum_{i=2}^{n} (X_i - E(X_i|X_{i-1}))^2 = \sum_{i=2}^{n} (X_i - \alpha X_{i-1} - (1-\alpha)\mu)^2 \; \ldots (3)$$

Were, μ and α are obtained by solving $\partial \mathbb{Q}_n(\theta)/\partial\theta = 0$:-

$$\hat{\alpha}_{CLS} = \frac{\sum_{i=2}^{n} X_i X_{i-1} - \frac{1}{n-1}\sum_{i=2}^{n} X_i \sum_{i=2}^{n} X_{i-1}}{\sum_{i=2}^{n} X_{i-1}^2 - \frac{1}{n-1}(\sum_{i=2}^{n} X_{i-1})^2} \; \ldots (4)$$

$$\hat{\mu}_{CLS} = \frac{\sum_{i=2}^{n} X_i - \hat{\alpha}_{CLS} \sum_{i=2}^{n} X_{i-1}}{(n-1)(1-\hat{\alpha}_{CLS})} \; \ldots (5)$$

2.3 Yule-Walker (YW):

The Yule-Walker method, introduced by Al-Osh and Alzaid (1987) and further developed by Du and Li (1991) and Jin-Guan & Yuan (1991), estimates the parameters of the INAR (1) model using the method of moments. This approach relies on the Yule-Walker equations, which use the autocorrelation function of the time series to derive parameter estimates.

The parameter $\hat{\alpha}_{YW}$ is derived as a function of the autocorrelation:

$$\hat{\alpha}_{YW} = \frac{\hat{\gamma}_1}{\hat{\gamma}_\circ} = \frac{cov(X_t, X_{t-1})}{Var(X_t)} \; \ldots (6)$$

$$\frac{\sum_{t=2}^{n} (X_t - \bar{X})(X_{t-1} - \bar{X})}{\sum_{t=1}^{n} (X_t - \bar{X})^2} \; \ldots (7)$$

Here, $\bar{X}$ is the sample mean of the process $\{X_t\}$, calculated as:

$$\hat{\mu}_{YW} = \bar{X} = \frac{1}{n}\sum_{t=1}^{n} X_t \; \ldots (8)$$

2.4 Conditional maximum likelihood (CML)

The Conditional Maximum Likelihood (CML) method is a fundamental approach for estimating the parameters of the INAR (1) process. The likelihood function for a sample of n observations from the INAR (1) process can be formulated as follows (Bourguignon et al., 2019b).

The likelihood function for the Conditional Maximum Likelihood (CML) method is given by:

$$L(\alpha;\lambda) = P(Y_1)\prod_{t=2}^{n} \Pr(Y_t|Y_{t-1}) \quad \ldots (9)$$

Where the conditional probability $Pr(Y_t|Y_{t-1})$ is expressed as:

$$Pr(Y_t|Y_{t-1}) = \sum_{i=0}^{min(Y_t|Y_{t-1})} \binom{Y_{t-1}}{i} \alpha^i (1-\alpha)^{Y_t - i} \frac{e^{-\lambda}\lambda^{Y_t - i}}{(Y_t - i)!} \quad \ldots (10)$$

The marginal distribution of the Poisson Integer Value Autoregressive (PoINAR (1)) process follows a Poisson distribution with mean $\lambda/(1-\alpha)$, the unconditional likelihood function then:

$$L(\alpha;\lambda) = \frac{e^{-\lambda/(1-\alpha)}[\frac{\lambda}{1-\alpha}]^{Y_1}}{(Y_1)!}\prod_{t=2}^{n}\left[\sum_{i=0}^{min(Y_t|Y_{t-1})} \binom{Y_{t-1}}{i} \alpha^i (1-\alpha)^{Y_t - i} \frac{e^{-\lambda}\lambda^{Y_t - i}}{(Y_t - i)!}\right] \ldots (11)$$

Assuming that Y_1 is given, the conditional likelihood function simplifies to:

$$L(\alpha;\lambda) = \prod_{t=2}^{n}\left[\sum_{i=0}^{min(Y_t|Y_{t-1})} \binom{Y_{t-1}}{i} \alpha^i (1-\alpha)^{Y_t - i} \frac{e^{-\lambda}\lambda^{Y_t - i}}{(Y_t - i)!}\right] \ldots (12)$$

The estimators for the maximum unconditional and conditional likelihoods can be obtained by maximizing the logarithms of the likelihood functions corresponding to equations (11) and (12), respectively. Al-Osh and Al-Zaid (1987) applied Sprott's (1983) method to eliminate one of the parameters in the derivative of the logarithmic likelihood function (Bourguignon et al., 2019a). The derivatives of the log-likelihood functions are given by:

$$\frac{\partial \log[L(\alpha,\lambda)]}{\partial \lambda} = \sum_{t=2}^{n} H(t) - (n-1) = 0 \quad \ldots (13)$$

$$\frac{\partial \log[L(\alpha,\lambda)]}{\partial \alpha} = \sum_{t=2}^{n} \frac{(Y_t - \alpha Y_{t-1} - \lambda H(t)}{\alpha(1-\alpha)} \quad \ldots (14)$$

Where $H_t = PY_{t-1}/PY_t$. From equation (14), the estimate for λ is:

$$\hat{\lambda} = \frac{\sum_{t=2}^{n} Y_t - \alpha Y_{t-1}}{n-1} \quad \ldots (15)$$

2.5 Support Vector Regression (SVR)

Support Vector Regression (SVR) is an innovative method for time series prediction, which plays a crucial role in accurate data modeling. It involves mapping data into a higher-dimensional space using kernel methods, facilitating linear regression within this transformed environment. The inputs to the SVR are transformed into a high-dimensional feature space by a nonlinear function. The decision function of the SVR model can be expressed as follows (Hu, 2017; Lee & Lee, 2021):

$$y = <\omega, \varphi(x)> + b \quad \ldots (36)$$

Where $\varphi(x)$ represents the nonlinear mapping of the inputs x, ω and b are constant vectors.

The main objective of the SVR algorithm is to determine the optimal values of the coefficients w and b in the regression function. The objective function and constraints are as follows (Hu, 2017; Ali & Mohammed, 2023):

Minimize $\frac{1}{2} \parallel \omega \parallel^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^{*}) \quad \ldots (34)$

Subject to the constraints:

$$\begin{cases} y_i - < \omega, \phi(x_i) > -b \le \varepsilon + \xi_i \\ < \omega, \phi(x_i) > +b - y_i \le \varepsilon + \xi_i{}^* \\ \xi_i, \xi_i{}^* \ge 0 \end{cases} \quad \dots (35)$$

Where ξ_i *and* $\xi_i{}^*$ represent the elastic variables measuring the error in training above and below the margin, and C is the positive penalty coefficient that controls the degree of penalty imposed for training errors. Nonlinear support vector regression can also be framed as a binary optimization problem using Lagrange multipliers after minimizing equation (35). The resulting nonlinear SVR binary optimization problem becomes:

$$\max \ -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i{}^* - \alpha_i)(\alpha_j{}^* - \alpha_j)\, k < x_i, x_j > + \sum_{i=1}^{n} y_i(\alpha_i{}^* - \alpha_i) - \sum_{i=1}^{n}\varepsilon(\alpha_i + \alpha_i{}^*) \dots (36)$$

With the constraints:

$$0 \le \alpha_i, \alpha_i{}^* \le c \ \dots (37)$$

$$\sum_{i=1}^{l}(\alpha_i{}^* - \alpha_i) = 0 \dots (38)$$

where $k(x_i, x_j)$ is the kernel function, which is the inner product $(\phi(x_i), \phi(x_j))$. The most commonly used kernel function is the Radial Basis Function (RBF), also known as the Gaussian kernel .(Kiwon, 2019), which is defined as:

$$k(x_i, x_j) = (\phi(x_i), \phi(x_j)) = \exp(-\gamma \left\| x_i - x_j \right\|^2)$$

Where $\left\| x_i - x_j \right\|^2$ denotes the squared Euclidean distance between the feature vectors $x_i$and x_j, and γ is the width parameter of the Gaussian kernel. By solving equation (37) with the given constraints, the regression function is expressed as (Ali & Mohammed, 2023)

$$f(x) = \sum_{i=1}^{l}(a_i - a_i^*)k(x_i, x_j) + b \qquad \dots (39)$$

2.6 Genetic algorithm (GA):

Genetic algorithms (GA) are a class of optimization algorithms that seek to maximize or minimize a given objective function, aiming to find the optimal solution to a computational problem. These algorithms are inspired by biological processes such as natural selection and reproduction. While the processes in GAs are often stochastic, they offer flexibility in controlling the level of randomness. The concept of genetic algorithms was first introduced by Holland in 1975, and it has since evolved into a powerful tool for solving optimization and search problems (Redha & Hadia, 2020; Jassim Lazem, 2018; Carr, 2014; Chudasama et al., 2011). Genetic algorithms typically consist of several stages: initialization, evaluation, selection, crossover, mutation, update, and execution. The evaluation stage generates a new set of chromosomes using genetic operators such as crossover and mutation (Sabah & Jasim, 2019; Sivanandam et al., 2008; Soni & Kumar, 2014).

2.6.1 (GA_SVR):

In the context of optimizing the parameters of the SVR algorithm, the fitness function is used to assess the effectiveness of the chosen parameters. The performance of the SVR model can be enhanced by adjusting its parameters, thereby improving the accuracy of the model. The fitness function evaluates the prediction accuracy using the SVR model with the selected parameters, allowing automated performance optimization (Ali & Mohammed, 2023; Firas & Moamen, 2020).

2.6.2 Proposed Method: (INAR (1)-SVR):

Common methods such as CLS, CML, and YW are used to generate predictions in INAR models, but these predictions may lack sufficient accuracy. To enhance prediction quality, we apply the SVR algorithm, using the predictions from these three methods as inputs to optimize them. SVR learns the relationship between these predictions and the actual values, resulting in more accurate predictions and improved overall model performance. The process is as follows:

1. Calculate the original predictions using CLS, CML, and YW.
2. Use the predictions as inputs for SVR.
3. Train the SVR model on the predictions and the actual values as targets.
4. Compute the Mean Squared Error (MSE) comparison before and after applying SVR and evaluate performance.

2.6.3 Proposed Method (INAR (1)-SVR-GA)

To optimize the SVR parameters using GA, the following steps are followed:

1. Parameter encoding: Represent the parameters C, ε, and γ as chromosomes.
2. Performance evaluation: Train and evaluate SVR using MSE and MAE.
3. Best selection: Select the best solutions.
4. Crossover: Combine parameters to form new solutions.
5. Mutation: Slightly modify some parameters to improve results.
6. Iteration: Repeat the process until the optimal parameters are identified.

3. Discussion of Results:

3.1 Simulation:

MATLAB statistical programming was used to write the simulation program. The program includes four main stages for estimating the INAR (1) model:

Stage **1: Define Default Values**

Two different values of $\boldsymbol{\alpha}$ were selected based on the knowledge of its influence on each method: $\alpha = 0.7$ *and* $\alpha = 0.3$. The error was generated following a Poisson distribution with λ=1. Three different sample sizes were used in this study: 100, 200, and 300.

Stage **2: Generate Data**

A time series for the INAR (1) model was generated, with the random error following a Poisson distribution. The fitness function for mean squared error was applied.

Stage **3: Estimation**

Model parameters were estimated using the selected methods: CLS, CML, YW, SVR, and SVR-GA.

Stage **4: Method Comparison**

In this stage, various estimation methods were compared using the Mean Squared Error (MSE) and Mean Absolute Error (MAE). The experiment was repeated 1,000 times, with the following formula used for comparison:

Table 1: MSE of the model for different methods when n =100 and $\alpha = 0.3$, $\lambda = 1$

Method	classical	SVR	SVR_GA
Yule-Walker	1.5608	1.4445	1.4135
CLS	1.5550	1.4422	1.4067
CML	1.5675	1.4377	1.4122

Table 2: MSE of the model for different methods when n=200 and $\alpha = 0.3, \lambda = 1$

Method	classical	SVR	SVR_GA
Yule-Walker	1.5750	1.4756	1.4559
CLS	1.5684	1.4713	1.4533
CML	1.5852	1.4742	1.4579

Table 3: MSE of the model for different methods when n=300 and $\alpha = 0.3, \lambda = 1$

Method	classical	SVR	SVR_GA
Yule-Walker	1.5884	1.5015	1.4623
CLS	1.5939	1.5041	1.4781
CML	1.5967	1.5022	1.4492

Table 4: MSE of the model for different methods when n=100, $\alpha = 0.7, \lambda = 1$

Method	classical	SVR	SVR_GA
Yule-Walker	2.4192	2.1588	2.1369
CLS	2.3990	2.1321	2.1295
CML	2.3756	2.1344	2.1207

Table 5: MSE of the model for different methods when n=200, $\alpha = 0.7, \lambda = 1$

Method	classical	SVR	SVR_GA
Yule-Walker	2.4338	2.2288	2.1769
CLS	2.4187	2.2165	2.1495
CML	2.4001	2.2270	2.1490

Table 6: MSE of the model for different methods when n=300 and $\alpha = 0.7, \lambda = 1$

Method	classical	SVR	SVR_GA
Yule-Walker	2.4057	2.2336	2.1983
CLS	2.4153	2.2310	2.1704
CML	2.3875	2.2255	2.1517

The results derived from the data presented in the tables indicate that the (SVR-GA) method generally outperforms other methods in most cases. Specifically, the data reveal that as the value of α increases, there is a corresponding rise in the values of the Mean Squared Error (MSE). This suggests that the (CML) approach demonstrates relatively higher discriminative power compared to traditional methods such as (CLS) and (YW) when α is increased. Overall, the findings highlight that the (CML) approach exhibits superior performance under these conditions.

4. Conclusions

Analysis based on the data shown in the tables:

A. The results generally suggest that the proposed method yields the most accurate estimates, outperforming the other estimation methods.

B. When compared to traditional methods, the CML method demonstrates superior performance. The proposed method, specifically at α=0.7 with λ=1, proves to be the most effective.

C. Overall, the results show that artificial intelligence algorithms outperform traditional methods such as CLS, YW, and CML.

D. The proposed (SVR-GA-CML) method consistently outperformed both the (SVR-GA-CLS) and (SVR-GA-YW) methods in the simulation model.

E. The results indicated that, with the exception of the sample size of 100, and when α=0.3 and λ=1, the (SVR-GA-CML) technique outperformed all other methods, making the (SVR-GA-CLS) method the best in this specific scenario.

F.The simulation results also revealed that the SVR method significantly improved predictions across all three methods.

Authors Declaration:

Conflicts of Interest: None

-We Hereby Confirm That All The Figures and Tables In The Manuscript Are Mine and Ours. Besides, The Figures and Images, which are Not Mine, Have Been Permitted Republication and Attached to The Manuscript.

- Ethical Clearance: The Research Was Approved by The Local Ethical Committee in The University.

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