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A NOVEL MONITORING APPROACH USING SUPPORT VECTOR REGRESSION METHOD FOR OPTIMIZING A TRIPLE-CONCEPT MODEL WITH AUTOCORRELATED DATA

Abstract: *Integrating production, maintenance, and quality concepts has yielded positive results for imperfect processes that degrade over time due to various specific causes. In practice, identified correlations within monitored data over time challenges the traditional assumption of independence. To address this, the Autoregressive Moving Average (ARMA) control chart has been utilized in integrated models. This study proposes a novel control chart based on the support vector regression (SVR) method to apply within integrated models. In an integrated model, the performance of both monitoring techniques are assessed. A solution procedure based on particle swarm optimization (PSO) algorithm is employed. An industrial case study and comparative analyses are presented for further examination. Under smaller shifts, SVR performs better, whereas monitoring with the ARMA chart yields infeasible solutions in six scenarios. However, due to the time-consuming procedure of the SVR, the ARMA chart becomes a more desirable option for larger shifts.*

Keywords: *autocorrelation, ARMA chart, support vector regression, production, maintenance*

1. Introduction

In statistical process control (SPC), control charts have increasingly gained acceptance in leading industries as effective tools for ensuring quality and reducing manufacturing costs. These charts are primarily utilized to detect process changes before large quantities of defective items are produced. Unlike processes that assume independence, many real-world processes exhibit correlation patterns among data points. Unidentified autocorrelation can degrade monitoring performance and lead to additional costs when using traditional monitoring techniques. This challenge has driven the development of specialized monitoring techniques for autocorrelated processes. Among these, the autoregressive moving average (ARMA) control chart stands out as a suitable option for monitoring autocorrelated processes (Jafarian et al., 2021, 2024a, 2024b).

This study aims to develop a novel control chart that swiftly detects abnormal patterns. To achieve this, we leverage Machine Learning (ML) techniques, which effectively learn from historical data. ML offers valuable insights without significant resource demands, finding widespread application in SPC across various domains. Promising ML approaches include variational autoencoders (Sergin & Yan, 2021), clustering (Lee et al., 2022), Convolutional Neural Networks (CNNs) (Xu et al., 2019), and Artificial Neural Networks (ANNs) (Yeganeh et al., 2023), often outperforming traditional statistical methods.

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While limited research exists on ML implementation in monitoring ARMA processes, this study aims to make original contributions by applying ML to ARMA processes. Our proposed method integrates ARIMA based chart statistics with the well-established support vector regression (SVR) technique to enhance out-of-control (OOC) detection capabilities, as measured by the average run length (ARL) criterion. The previous literature includes several SVR-based control charts, such as those by Cuentas et al. (2017), Lee and Kim (2018), Yeganeh et al. (2024), and Hric and Sabahno (2024). Our proposed control chart introduces a unique SVR-based method for monitoring ARMA processes. This involves defining and extracting informative input features, which are subsequently used to train an SVR model offline. Once trained, these models are applied to monitor the process in real time and identify any OOC states. The approach significantly contributes to improving both the selection of input features and the training methodology, thereby enhancing the model's sensitivity to detecting OOC states.

In addition to enhancing quality, modern production systems must also focus on minimizing downtime and reducing operating costs. In these imperfect processes, integrating three key components, including SPC, maintenance policy (MP), and economic production quantity (EPQ), has yielded significant benefits for the overall system. Under independence assumption of data, Shojaee et al. (2024) further advanced this field by proposing a model to monitor simple linear profiles, resulting in significant cost reductions and improved operational efficiency. Salmasnia et al. (2023) developed a bi-objective model integrating triple concepts with warranty and pricing strategies. Their employed a non-central chi-square control chart for monitoring. Salmasnia et al. (2024a) proposed an integrated model for multi-component systems with series-parallel configurations. They used an X-bar control chart and structural importance measures to reduce costs while addressing system complexity. Additionally, Salmasnia et al. (2024b) proposed an integrated model for a two-stage cascade process with multiple assignable causes and random failures, using a Cause-selecting control chart and various maintenance policies. Their results indicate significant cost savings and improved system performance.

Under autocorrelation, only three studies have explored integrated modeling as follows. Jafarian-Namin et al. (2021) optimized an integrated model of the triple components across ten scenarios by incorporating a delayed monitoring policy and utilizing the ARMA control chart. More recently, Jafarian-Namin et al. (2024a) proposed another integrated model, evaluating its performance in three scenarios. Their findings demonstrated the superior performance of the ARMA control chart compared to the mixed EWMA-CUSUM, EWMAST, and special cause control charts. Furthermore, by introducing uncertainty in estimating input factors, Jafarian-Namin et al. (2024b) developed robust designs for two simple and integrated models, comparing the effectiveness of the ARMA and acceptance control charts.

This research introduces a novel control chart utilizing the SVR method. It is then incorporated into integrated modeling. Within the framework of the integrated model, the effectiveness of the proposed control chart is compared with that of the ARMA chart, as well as their respective contributions to cost reduction. The structure of this manuscript is as follows. The next section provides an overview of monitoring techniques for autocorrelated processes. Section three presents a detailed explanation of the integrated model. In section four, the particle swarm optimization (PSO) solution approach is introduced. Subsequently, an industrial case study and comparative analyses are presented in section five for further evaluation. Finally, the conclusions and potential future directions are outlined.

2. Monitoring techniques

Consider a univariate autocorrelated ARMA process with a mean of μ. The value at time t can be expressed using the ARMA(1,1) model as follows:

$$X_t = C + uX_{t-1} + a_t - va_{t-1}$$

where C represents a constant, X_{t-1} denotes the actual value at time t-1, and a_t and a_{t-1} are random error terms distributed as $N(0,\sigma_a^2)$. Additionally, u and v are the parameters for the autoregressive (AR) and moving average (MA) components, respectively. The variance of ARMA(1,1) model can be determined as follows:

$$\sigma_X^2 = \frac{1 - 2uv + v^2}{1 - u^2}$$

In the remainder of this section, the ARMA and SVR control charts are presented for monitoring ARMA(1,1) processes.

2.1. ARMA control chart

Consider L as a coefficient. The upper and lower control limits of the ARMA chart are defined as:

$$UCL = \mu + L\sigma_Z$$
$$LCL = \mu - L\sigma_Z$$

where:

$$\sigma_Z^2 = \left[\frac{2(\theta - \phi)(1 + \theta)}{1 + \phi} + 1\right]\sigma_X^2$$

This control chart monitors the following statistic (where θ_0=1+θ-ϕ, with ϕ and θ representing the AR and MA parameters, respectively):

$$Z_t = \phi Z_{t-1} + \theta_0 X_t - \theta X_{t-1}$$

To compute the ARL values for in-control (IC) and OOC states, denoted as ARL_0 and ARL_1, respectively, a simulation procedure is employed, following the method described by Jafarian et al. (2024a).

2.2. SVR method

In 1995, Vapnik introduced the Support Vector Machine (SVM), a groundbreaking ML method designed to address limitations of ANNs, particularly in classification tasks. SVM's core principle revolves around minimizing the training error while simultaneously controlling the model's complexity (empirical or structural risk minimization). To achieve this, non-linear problems are transformed into higher-dimensional spaces (mapped to a hyperplane) where optimal separation between classes is sought. This involves maximizing the geometric margins between classes while minimizing classification errors. While SVM excels in binary classification, extensions are necessary for multi-class problems and regression tasks. This paper focuses on using SVR for monitoring the ARMA process for the first time, which is briefly outlined here. For a more in-depth exploration of SVR for monitoring profiles, readers are referred to Yeganeh et al. (2024).

SVR is a powerful machine learning algorithm derived from the SVM framework. Unlike traditional SVM, which focuses on classification, SVR aims to predict continuous values. It achieves this by defining an "epsilon-insensitive" loss function. This function penalizes predictions that deviate from the actual values by more than a specified margin (epsilon). SVR seeks to find a function that minimizes the sum of the errors within this margin while simultaneously controlling the model's complexity. This approach leads to robust and accurate predictions, making SVR a valuable tool for various regression problems in fields like finance, engineering, and time series analysis. The SVR training and evaluation process involves preparing the dataset by cleaning, engineering features, and splitting it into training and testing sets. The model is then trained on the training data using selected hyperparameters, and its performance is evaluated on the unseen test data using metrics like Mean Squared Error (MSE) and R-squared. Hyperparameter tuning can be performed to optimize the model's performance, followed by retraining and re-evaluation.

3. Model description

Considering the three scenarios in Fig. 1, the integrated total cost function is defined as follows:

$$ETC = E(Q) + E(Sa) + E(M) + E(I)$$

where the terms for quality loss, sampling, maintenance, and inventory-related costs are defined as follows, respectively:

$$E(Q) = \sum_{r=1}^{3} E\left(C_Q \middle| Sc_r\right) Pr(Sc_r)$$

$$E(Sa) = \sum_{r=1}^{3} E(C_S|Sc_r)\, Pr(Sc_r)$$

$$E(M) = \sum_{r=1}^{3} E(C_M|Sc_r)\, Pr(Sc_r)$$

$$E(I) = \frac{B \times E(T) \times (p-d)}{2} + \frac{D \times A}{p \times E(T)}$$

Table 1 lists the applied notations (for more details, refer to Jafarian et al. (2024a)). By dividing the *ETC* in (6) by *E*(*T*), the expected hourly cost (*EHC*) is obtained. Thus, the integrated model is expressed as follows:

$$\begin{gathered} \min EHC \\ s.t. \\ ARL_0 \geq ARL_0^{min} \\ ARL_1 \leq ARL_1^{max} \\ kh \geq R_{Int} \\ nE \leq h \\ Bounded\ decision\ variables \end{gathered}$$

where the ARL values are constrained to achieve desirable ones. The lower bound of R_{Int} ensures the continuity of the process. The fourth constraint guarantees the feasibility of the results. Checking time of simple size *n* must not exceed *h* time units. To obtain an unconstrained model for solving via PSO, the penalized OBF is defined as follows (S indicates a solution, and $viol_{vi}$ represents the violation terms for the vi^{th} constraint from its right-hand-side, where *vi*=1,2,3,4):

$$fp(S) = EHC(S) \times \left(1 + viol_1(S) + viol_2(S) + viol_3(S) + viol_4(S)\right)\#$$

Table 1. Notations of integrated modeling

Notation	Description
$E(C_Q\|Sc_r)$	Expected quality loss cost for each scenario
$E(C_S\|Sc_r)$	Expected sampling cost for each scenario
$E(C_M\|Sc_r)$	Expected maintenance cost for each scenario
$Pr(Sc_r)$	Probability of occurring the r^{th} scenario
E(T)	Expected time of process cycle
A	Ordering cost
B	Inventory holding cost
D	Total demand
p	Production rate
d	Daily demand

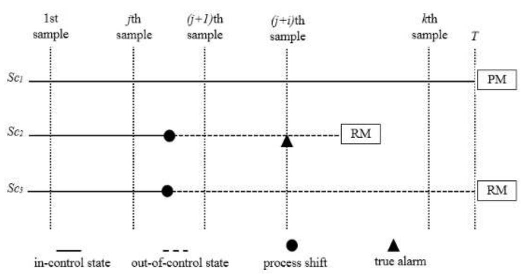

Figure 1. Scenarios

4. Solution procedure

The fitness value of each particle is assessed by the penalized OBF, $fp(Prt_y^r)$, for *y*=1, 2,…, N_P. During the optimization process, a particle's movement is guided by its: (1) current velocity, personal best (*pbest*), and (3) global best (*gbest*). To determine the *pbest*, if $fp(Prt_y^r) \leq fp(pbest_y^{r-1})$, the best position experienced by y^{th} particle is updated to $pbest_y^r \rightarrow Prt_y^r$. To determine the *gbest*, if $fp(pbest_y^r) \leq fp(gbest^{r-1})$ for *y*=1, 2,…, N_P, the best solution among all particles is set to $gbest^r \rightarrow pbest_y^r$. Afterward, the stopping criterion is evaluated. If $r=N_I$, the $gbest^r$ becomes the optimal solution. Else, the iteration continues by setting *r*=*r*+1 and generating two random numbers r_p, and r_g, uniformly distributed between (0,1). The velocities and positions are then updated. Note that the models are solved in MATLAB software (version R2016b). Moreover, we set *w*=1, (c_1, c_2)=(2, 2), N_P=80, and N_I=150 for optimization.

5. Experimental results

Table 2 presents the nominal parameters of an industrial example adapted from Jafarian et al. (2024a). For shift sizes of δ=1.2, 1.5, and 2, Table 3 represents the optimal solutions of employing both ARMA and SVR monitoring techniques. At δ=1.2, applying SVR results in a maximum saving of 80.33 in *EHC*. However, employing the ARMA chart at δ=1.2 leads to an infeasible solution because ARL_1=12.07 exceeds its threshold. Utilizing the SVR brings a saving of 35.66 in *EHC* decreases to at δ=1.5. However, at δ=2.0, utilizing the ARMA chart becomes desirable.

Table 2. Nominal parameters

Parameter	μ	σ_x^2	u
Value	100	10	0.475
Parameter	v	E	p
Value	0.00	0.01	100
Parameter	d	D	A
Value	80	10000	60
Parameter	B	R_{Int}	
Value	10	5	
Parameter	ARL_0^{min}	ARL_1^{max}	
Value	200	10	

Upon examining the detailed results in Tables 4, 5, and 6, several key findings emerge regarding the comparative performance of the ARMA and SVR methods, as outlined below:

1. *EHC* trend:
   - SVR generally shows lower *EHC* compared to ARMA, indicating that SVR is more cost-efficient under lower values of δ.
   - As δ increases, *EHC* for both methods tends to increase.
   - SVR maintains more stable *EHC* values across varying u and v. Higher values of v often lead to increased *EHC* for ARMA, while SVR remains less sensitive.
   - The utilization of the ARMA chart results in infeasible solutions for four designs in Table 4 and two designs in Table 5.
2. ARL_0 trend:
   - ARMA achieves higher ARL_0 values, meaning it has better false alarm control compared to SVR.
   - ARMA's ARL_0 shows more variability across u and v, while SVR remains consistent.
3. ARL_1 trend:
   - ARMA exhibits lower ARL_1 values under δ=2.0, indicating faster detection of shifts.
   - Lower δ values lead to higher ARL_1 for ARMA compared to SVR.
   - ARL_1 for ARMA decreases significantly as v increases, while SVR's ARL_1 remains relatively constant.

Table 3. Comparison between two monitoring techniques in triple-concept integrated model

δ	Control chart	*EHC*	ARL_0	ARL_1
1.2	ARMA	451.97	203.37	12.07
	SVR	371.64	227.56	6.48
1.5	ARMA	407.30	217.37	8.94
	SVR	371.64	227.56	6.48
2.0	ARMA	368.29	230.97	5.56
	SVR	371.92	212.34	6.22

Table 4. Comparison between two monitoring techniques in triple-concept integrated model under different ARMA parameters and δ=1.2

u	v	Control chart	EHC	ARL_0	ARL_1
0.00	0.00	ARMA	373.07	226.94	6.63
		SVR	370.00	213.28	6.30
	0.25	ARMA	364.75	233.61	4.68
		SVR	369.13	212.74	6.08
	0.50	ARMA	359.29	272.86	3.37
		SVR	369.34	213.28	6.16
	0.75	ARMA	354.93	290.04	2.62
		SVR	369.24	213.28	6.46
0.25	0.00	ARMA	406.24	201.61	9.17
		SVR	371.50	209.12	6.18
	0.25	ARMA	372.01	213.12	6.64
		SVR	369.53	260.92	6.32
	0.50	ARMA	364.01	234.11	4.24
		SVR	369.43	213.28	6.24
	0.75	ARMA	358.01	218.08	3.05
		SVR	373.53	213.28	6.44
0.50	0.00	ARMA	470.10	203.97	13.35
		SVR	371.64	227.56	6.48
	0.25	ARMA	538.11	204.57	9.66
		SVR	369.11	209.48	6.06
	0.50	ARMA	374.63	244.34	6.52
		SVR	369.52	213.28	6.44
	0.75	ARMA	361.57	325.39	4.11
		SVR	369.90	212.66	6.24
0.75	0.00	ARMA	500.47	210.91	22.48
		SVR	369.83	207.80	6.12
	0.25	ARMA	520.80	208.89	25.30
		SVR	369.65	222.32	5.98
	0.50	ARMA	489.71	200.06	13.14
		SVR	368.70	207.22	6.06
	0.75	ARMA	375.63	277.98	7.03
		SVR	368.97	213.28	6.30

Table 5. Comparison between two monitoring techniques in triple-concept integrated model under different ARMA parameters and δ=1.5

u	v	Control chart	EHC	ARL_0	ARL_1
0.00	0.00	ARMA	365.99	280.08	4.86
		SVR	372.25	211.30	6.44
	0.25	ARMA	358.21	215.77	3.35
		SVR	369.14	210.60	6.16
	0.50	ARMA	356.92	309.03	2.63
		SVR	369.40	213.28	6.50
	0.75	ARMA	352.76	597.30	2.32
		SVR	372.08	213.28	6.40
0.25	0.00	ARMA	375.19	222.93	6.89
		SVR	368.31	209.48	6.12

u	v	Control chart	EHC	ARL_0	ARL_1
	0.25	ARMA	363.73	308.97	4.93
		SVR	369.52	213.28	6.44
	0.50	ARMA	361.00	250.81	3.36
		SVR	369.26	212.66	6.26
	0.75	ARMA	354.68	533.90	2.70
		SVR	370.75	213.28	6.68
0.50	0.00	ARMA	449.64	214.44	9.59
		SVR	371.64	227.56	6.48
	0.25	ARMA	381.40	227.98	7.76
		SVR	369.11	209.48	6.06
	0.50	ARMA	365.67	302.63	5.17
		SVR	369.52	213.28	6.44
	0.75	ARMA	358.44	223.94	3.06
		SVR	373.60	212.74	6.62
0.75	0.00	ARMA	451.19	213.58	15.87
		SVR	373.16	215.42	7.14
	0.25	ARMA	490.19	228.62	14.53
		SVR	370.68	213.28	6.66
	0.50	ARMA	382.27	216.49	9.43
		SVR	370.56	207.76	6.62
	0.75	ARMA	367.99	237.06	4.94
		SVR	370.44	215.42	6.78

Table 6. Comparison between two monitoring techniques in triple-concept integrated model under different ARMA parameters and δ=2.0

u	v	Control chart	EHC	ARL_0	ARL_1
0.00	0.00	ARMA	361.20	280.79	3.34
		SVR	372.25	211.30	6.44
	0.25	ARMA	352.26	378.27	2.48
		SVR	369.14	210.60	6.16
	0.50	ARMA	350.56	320.06	2.03
		SVR	371.16	309.20	7.06
	0.75	ARMA	349.47	290.30	1.71
		SVR	372.20	213.28	6.44
0.25	0.00	ARMA	364.77	225.69	4.15
		SVR	368.55	213.94	6.10
	0.25	ARMA	360.80	274.49	3.31
		SVR	371.52	213.28	6.16
	0.50	ARMA	351.90	263.95	2.38
		SVR	371.64	213.28	6.30
	0.75	ARMA	351.19	267.07	1.93
		SVR	369.87	215.42	6.36
0.50	0.00	ARMA	370.59	247.77	5.69
		SVR	367.62	210.66	5.78
	0.25	ARMA	364.44	212.64	4.08
		SVR	371.57	209.12	6.14
	0.50	ARMA	360.11	231.61	3.06
		SVR	369.53	260.92	6.32
	0.75	ARMA	351.81	337.06	2.30
		SVR	371.75	213.28	6.22
0.75	0.00	ARMA	411.57	206.25	9.15

u	v	Control chart	EHC	ARL_0	ARL_1
		SVR	370.85	204.20	5.72
	0.25	ARMA	385.05	283.70	8.71
		SVR	368.74	235.84	6.18
	0.50	ARMA	367.87	200.93	4.88
		SVR	368.08	211.80	5.88
	0.75	ARMA	357.41	250.83	3.09
		SVR	371.26	209.50	6.20

6. Conclusions

The specific characteristics of the monitored process can influence the relative performance of ARMA and SVR. In general, SVR outperforms ARMA due to its lower EHC across different scenarios with smaller shift sizes. However, the SVR procedure is time-consuming. For instance, with a shift size of 2, obtaining results using the ARMA and SVR methods takes approximately 94.38 and 6876.15 seconds, respectively. In summary, a comprehensive evaluation that considers the specific process characteristics, desired control objectives, and runtime duration is crucial for selecting the most suitable method.

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