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Optimal Call Failure Rates Modelling with Joint Support Vector Machine and Discrete Wavelet Transform

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Abstract: Failure modeling is an essential component of reliability engineering. Enhanced failure rate modeling techniques are vital to the effective development of predictive and analytical methodologies, demonstration of the engineering procedure, allocation of procedures, design, and control of procedures. However, failure rate modeling has not been given adequate treatment in the literature. The need to investigate failure rate modeling leveraging cutting-edge techniques cannot be overemphasized. This paper proposed and applied a joint support vector regression (SVR) and wavelet transform (WT) approach termed (WT-SVR) to training and learning the call failures rate in wireless system networks. The wavelet transform has been accomplished using the wavelet compression sensing technique. In this technique, the standardized call failure rate data first go through a wavelet filtering transformation matrix. This is followed by separating and outputting the transformed filtered components in the compression phase. Finally, the transformed filtered output components were trained and evaluated using the SVR based on statistical learning theory. The resultant outcome revealed that the proposed WT-SVR learning method is by far better than using only the SVR method for call rate prognostic analysis. As a case in point, the WT-SVR attained STD values of 0.12, 0.21, 2.32, 0.22, 0.90, 0.81 and 0.34 on call failure data estimation compared to the basic SVR that attained higher STD values of 0.45, 0.98, 0.99, 0.46, 1.44, 2.32 and 3.22, respectively.

Index Terms: Wavelet transform; Service quality; Failure rate; Failure modeling; Support Vector Machine**.**

1. Introduction

The wireless and mobile radio communication systems are designed and deployed to offer services at all times to the communication entities. Despite being introduced several years ago, GSM remained one of the most widespread and well subscribed to the communications technologies, especially voice telephony [1]. A report [2] revealed that the percentage of subscribers with the basic phone, mainly used for circuit-switched voice telephony, still outweighs that of the smartphone users in Sub-Sahara Africa, except in South Africa with 40:51%. Another report from the GSM Association (GSMA) [3] revealed that 747 million Subscriber Identity Module (SIM) connections had been recorded in sub-Saharan Africa, which is about 75% of the total global population.

The high recorded successes regarding voice telephony subscription and usage have also been devoid of high churn rates among subscribers due to poor service quality conditions and poor infrastructure management in some wireless communication networks [4], [5]. One key way to resolve service quality issues in operational networks is to monitor and optimize performance constantly [6], [7]. The call failure rate is one of the foremost service quality indicators utilized to monitor the performance of wireless radio networks [8]. For this crucial reason, works reported on call failure rate modeling and analysis are available [9]–[15]. In [9], a four-parameter fitting model has been applied to study failure rate curves. The results of the study proved the convenience and validity of the developed fitting model. In [11], [14], [15], the authors employed the modified Weibull and exponential distribution to model failure rates. Similar works on failure rate modeling using different probability distribution functions have been presented [16], [17]. Particularly, in [18], a hybrid based ANN-cascade scheme was proposed for predictive analysis of Healthcare data. However, the accuracy attained in terms of Mape was as high as 24.82. Such NN based cascade scheme was also employed in [19], but for missing sensor data recovery.

From the preceding literature, most works present either the SVR technique or the WT approach only, and the need for a hybrid model comprising the integration of the SVR and WT to train and learn call failure rates is not out of place. To this end, our main contributions in paper include:

- We presented a realistic boosted call failure rates modeling using a support vector machine with wavelet transform.
- In particular, we proposed and applied joint support vector regression (SVR) and wavelet transform (WT) to train and learn the rate of call failures using realistic wireless system networks data.
- The proposed hybrid model presents more accurate call failure rates data estimation acquired from an operational 4G LTE network than other standard approaches.

The remainder of this paper is structured as follows. Section 2 presents the theoretical background covering the wavelet transform, support vector regression, call failure rate and sample data. Section 3 details the proposed WT-SVR approach, data transformation, SVR training, and learning performance evaluation of the proposed WT-SVR technique. Section 4 presents the results and discussions, and Section 5 gives a concise conclusion to the paper.

2. Theoretical Background

The Wavelet transform and the Support Vector Regression are described in this section. In addition, the call failure rate and sample data are highlighted briefly.

2.1. Wavelet Transform

Wavelet transform (WT) has evolved as a distinctive technique to pre-treat (preprocess) and compress (scale) multivariate complex data. Mathematically, a wavelet can be defined by (1) [19].

$$\Psi(m,n) = \frac{1}{\sqrt{|m|}}\Psi\left(\frac{t-n}{m}\right) \tag{1}$$

where m and n designate the scale and dilation parameters.

The WT provides a direct transformation means to decompose a row vector p $(1 \times J)$ into a set of components called the approximation and coefficients utilizing a filter matrix denoted as W $(i \times J)$ defined in (2):

$$y = W.p \tag{2}$$

where p is the input vector of length $j \times 1$, y is the compressed output vector of length $i \times 1$, and W is $i \times j$ filter matrix.

Since, $p = \Psi x$, then equation (2) can be written as (3):

$$y_{WT} = W.p = W\Psi x \tag{3}$$

where x is the input data vector.

2.2. Support Vector Regression

In SVR, we seek a function f (x) that can produce a minimum deviation ε from the actual data target y_i during training. This implies that we care about minimizing the resultant deviation error, ε, after data training.

Now, let a measured dataset comprise $[(x_1, y_1),...,(x_i, y_i) \subset X \times R]$, training, where x_i and y_i articulate the input vector and the corresponding target output values, $i = 1,..., N$ for variables, with N being the data sample

number. Now, let us begin by considering a linear SVM function $f(x)$. Here, the input vector can be mapped into the outputs employing a known linear SVM function $f(x)$, which takes the form of (4):

$$f(x) = (\rho, \Phi(x_i) + b \text{ with } \rho \in X, b \in R \tag{4}$$

and which must be as flat as possible by seeking a small weight vector ρ, and b is the bias. One of the best ways to achieve this is to find $f(x)$, which minimizes the norm $(\rho'\rho)$. This can also be conveyed as a critical convex optimization problem to minimize subject to the residuals having a value $\leq \varepsilon$, given by (5):

$$\text{minimize } J(\rho) = \frac{1}{2}\langle \rho'\rho \rangle$$

subject to

$$\begin{aligned} y_i - \langle \rho, \Phi(x_i) \rangle - b \leq \varepsilon \\ \langle \rho, \Phi(x_i) \rangle + b - y_i \leq \varepsilon \end{aligned} \tag{5}$$

In order to cater to the infeasible constraints in equation (5), slack variables are introduced, leading to (6):

minimize $\frac{1}{2}\langle \rho'\rho \rangle + C\sum_{i=1}^{N} \xi_i + \xi_i^{\bullet}$

subject to

$$\begin{aligned} y_i - \langle \rho, \Phi(x_i) \rangle - b \leq \varepsilon + \xi_i, \ i = 1,\ldots,N \\ \langle \rho, \Phi(x_i) \rangle + b - y_i \leq \varepsilon + \xi_i^{\bullet}, \quad i = 1,\ldots,N \\ \xi_i, \xi_i^{\bullet} \geq 0, \ i = 1,\ldots,N \end{aligned} \tag{6}$$

where $\xi_i^{\bullet}$ and ξ_i are the slack variables. C is a constant, and it assists in subjecting overfitting. N represents the data sample number. The optimization problem mentioned above can be transformed to a dual Lagrangian problem by introducing Lagrange multiplier β_i and $\beta_i^{\bullet}$, and after some simplification, the regression function turns to (7):

$$f(x) = \sum_{i=1}^{N} (\beta_i - \beta_i^{\bullet}) \langle \Phi(x_i), \Phi(x) \rangle + b \tag{7}$$

One helpful technique to further transform the SVM regression model in equation (7) into higher dimensional space is by replacing the dot product $\Phi(x_i)\ \Phi(x)$ with a kernel function $\mathrm{H}(x_i, x)$, and this yields (8):

$$f(x) = \sum_{i=1}^{N} (\beta_i - \beta_i^{\bullet}) \mathrm{H}(x_i, x) + b \tag{8}$$

Table 1 shows the vital kernel functions types explored in this paper.

Table 1. Some kernel function names and formulae

	Kernel function name	Formula
1	Linear	$\mathrm{H}(x_i, x) = ((x_i, x) + 1)^d$
2	Polynomial	$\mathrm{H}(x_i, x) = (1 + x_i, x)^d$, where d defines the set $\{2,3\ldots,\}$
3	Gaussian	$\mathrm{H}(x_i, x) = \exp\left(-\lVert x_i - x \rVert^2\right)$

2.3. Call Failure Rate and Sample Data

The call failure rate (C_{FR}) is a statistical measure of the percentage of calls that are unable to go through or fail through the network after initiation from the caller. Mathematically, C_{FR} *can* be described by (9):

$$C_{AC} = [1 - C_{AR}(SDCCH) \times (1 - C_{DR}(SDCCH)) \times (C_{AR}(TCH)) \times (C_{DR}(TCH))] \tag{9}$$

where

$C_{AR}(SDCCH)$ = SDCCH Access Rate
$C_{DR}(SDCCH)$ = SDCCH Drop Rate
$C_{AR}(TCH)$ = TCH Access Rate
$C_{DR}(TCH)$ = TCH Drop Rate)
TCH = Traffic channel
SDCCH = Standard Dedicated Control Channel.

3. Proposed WT-SVR Approach

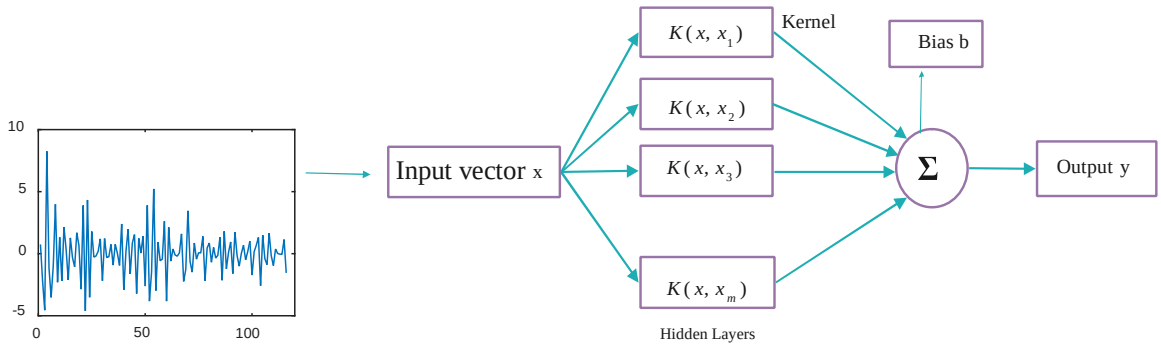
This study obtains extensive C_{FR} sample data from a commercial GSM/UMTS/LTE network operator in Port Harcourt City, Nigeria. The measurements took place from November 2019 to December 2019. The data consists of different GSM/UMTS network performance indicators. A seven-day call failure rate data obtained from 200 cells were selected to serve as representative sample data for analysis in this work. The proposed and applied joint support vector regression (SVR) and wavelet transform (WT) termed WT-SVR have been used to train and learn the rate of call failures derived from field measurements. The procedure is described in the following steps:

3.1. Data Transformation

In order to achieve better results during the analysis, the input data variables were preprocessed to have a similar scale and range. This is performed here using standardization and wavelet transforms techniques. In the standardization process, input data variables were scaled with a zero mean value and a standard deviation of 1. Then the standardized data input variables were further pre-treated using the wavelet transform technique. Here, the measurement vector first goes through a wavelet filtering transformation matrix, W. This is followed by separating and outputting the transformed filtered components in the compression step.

3.2. SVR Training and Learning

The SVR is a kernel-based machine learning technique [20]–[22]. Thus, we selected the three most common kernel functions; Gaussian kernel, linear kernel, and radial basis kernel**.** This step is followed by applying the WT component of the call failure rate data as an input vector for the SVR training and testing, as shown in Figure 1(a), and the SVR training process is illustrated in Fig. 1(b).



(a) WT input vector (b) SVR Architecture

Fig. 1. Proposed support vector regression combined with wavelet transform (WT-SVR)

3.3. Performance Evaluation of the Proposed WT-SVR Method

In order to evaluate the learning capability of the trained call failure rate data with the proposed WT-SVR approach, we employ five statistical indicators. These include the mean absolute error, normalized root mean square error, root mean square, and standard deviation errors [23]–[28]. Finally, the results are presented in Section 4 of this paper.

4. Results and Discussion

The resultant outcome of the training and learning of the call failure rate data are presented in this section. All data preprocessing, training, graphics, and evaluation were accomplished in MATLAB. First, statistical results are provided in Figure 2 and Table 2, showing the daily call failure rates based on its sampled data acquired from 200 cells in the cellular network investigated. From Table 1, day 2 recorded the highest call failure rate of 23.27%, followed by days 5 and 4 with 15.36% and 13.75% call failure rates, respectively. The least is recorded on day 1, followed by day 7 with 6.18% and 6.29% call failure rates, respectively. Generally, the mean call failure rate recorded for days 1 to 7 was lower

than the 2% performance threshold set by the performance management threshold specified by most telecom network operators and stakeholders. Also, the low variances recorded within the evaluation period are pretty low, as seen in Table 2. Perhaps, this indicates that the daily call failure rates fall around the mean values. However, the maximum failure rates recorded are taken for necessary action by the network operators.

Table 2. Statistical analysis of daily call failure rate data from 200 cells

Day	Minimum (%)	Maximum (%)	Mean (%)	Variance (%)
1	0.81	6.18	1.39	1.21
2	0.07	23.27	1.59	4.16
3	0.08	9.75	1.31	1.10
4	0.03	13.75	1.43	2.25
5	0.14	15.36	1.45	3.20
6	0.15	10.85	1.53	2.59
7	0.20	6.29	1.18	0.75

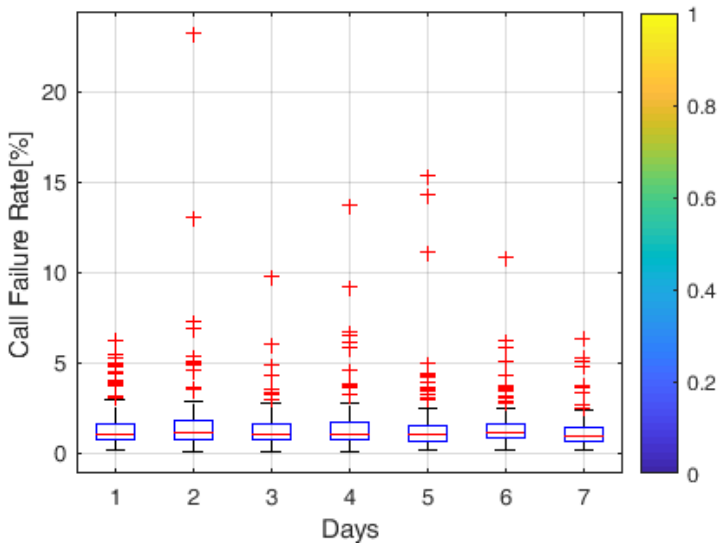


Fig. 2. Daily call failure rate data sampled from 200 cells

Additionally, we provide the call failure rate-adaptive learning performance using the projected WT-SVR model compared with the basic SVR model. We employed four key statistical evaluation indexes to examine their modeling and learning capabilities. The index includes standard deviation error (STD), Percentage Error (PE), Root Means Square Error (RMSE), and Mean Absolute Error (MAE). In our comparison, lower values with the indexes mean superior learning capabilities. Due to brevity, we only provide the learning made by the proposed WT-SVR model using the graphs plotted in Figs. 3 to 9. Specifically, the figures describe the adaptively learned call failure rate data with the proposed WT-SVR model for days 1 to 7, respectively. Nevertheless, the detailed learning superiority of the proposed WT-SVR on the acquired daily call failure rates over the basic SVR model is shown in Table 3 under different kernels.

It is shown from the tabulated results that the proposed WT-SVR performed far better than the standard SVR model with lower STD, PE, RMSE, and MAE values. For example, by means of the Gaussian kernel function, the WT-SVR attained STD values of 0.12, 0.21, 2.32, 0.22, 0.90, 0.81, 0.34 for days 1 to 7 call failure data compared to the basic SVR that attained 0.45, 0.98, 0.99, 0.46, 1.44, 2.32 and 3.22 STD values. Similar performances were attained using linear and polynomial kernels in correspondence with PE, RMSE, and MAE values. Finally, Table 4 presents the results that examined the effect of data size on the proposed WT-SVR learning accuracy. The results show that WT-SVR learning ability improves with increasing call failure rate data sizes from 50 to 200.

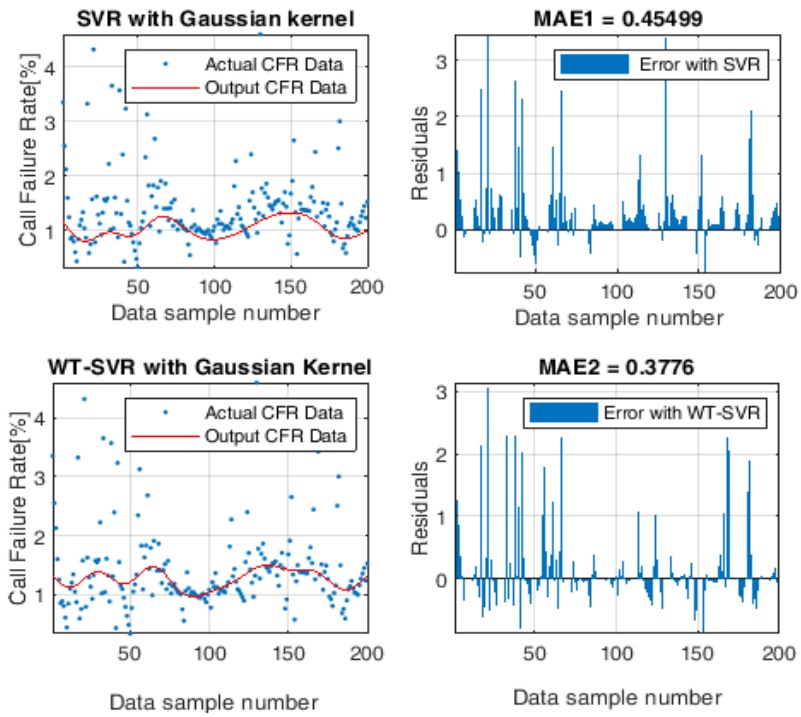


Fig.3. Adaptively learned call failure rate data with proposed WT-SVR model day 1

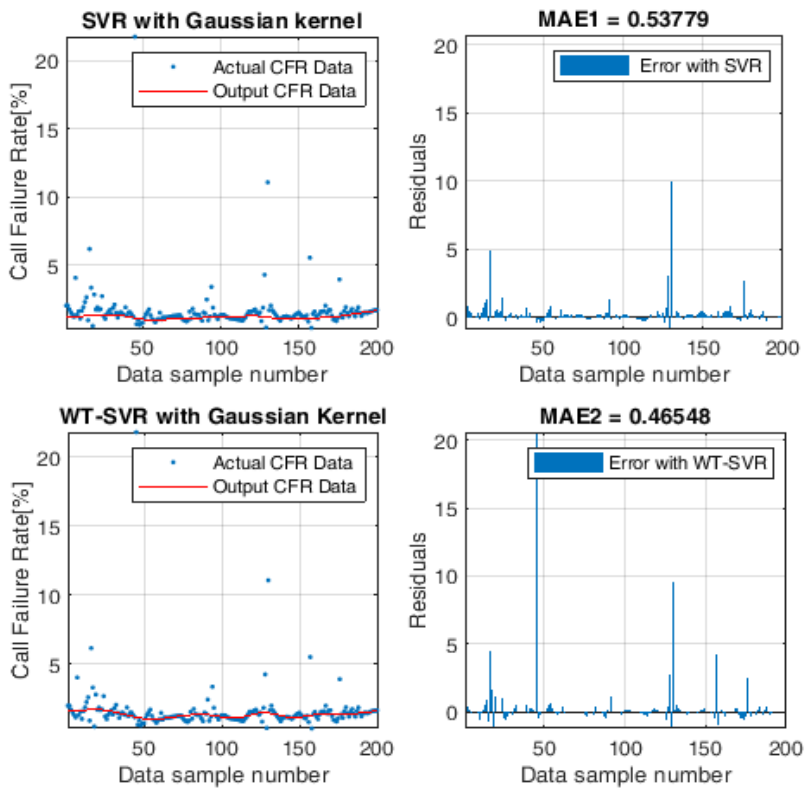


Fig. 4. Adaptively learned call failure rate data with proposed WT-SVR model day 2

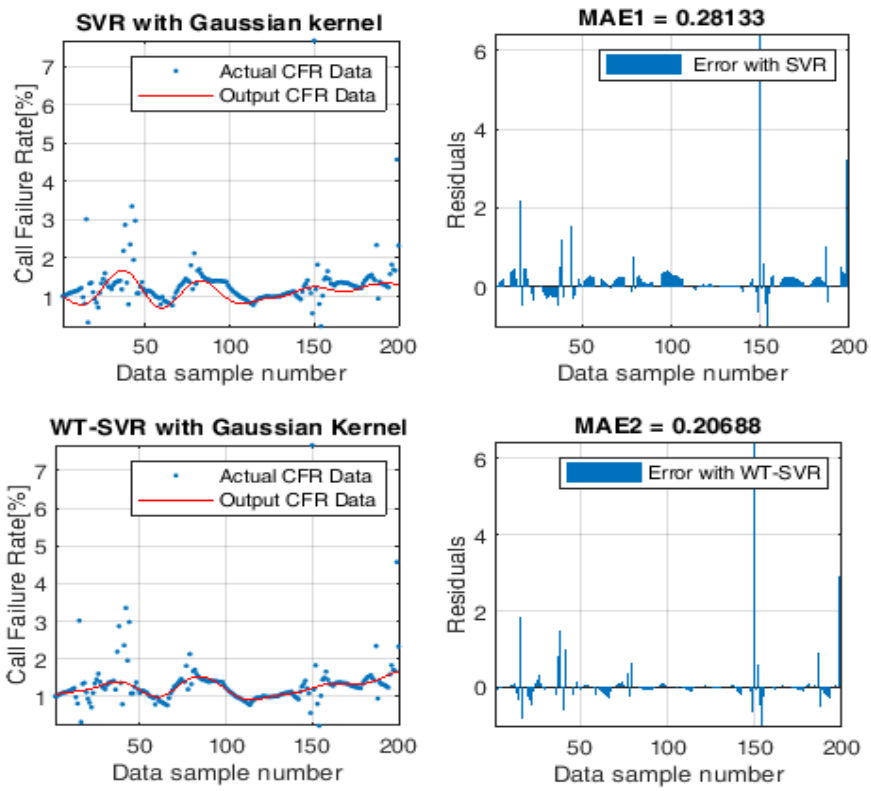


Fig. 5. Adaptively learned call failure rate data with proposed WT-SVR model day 3

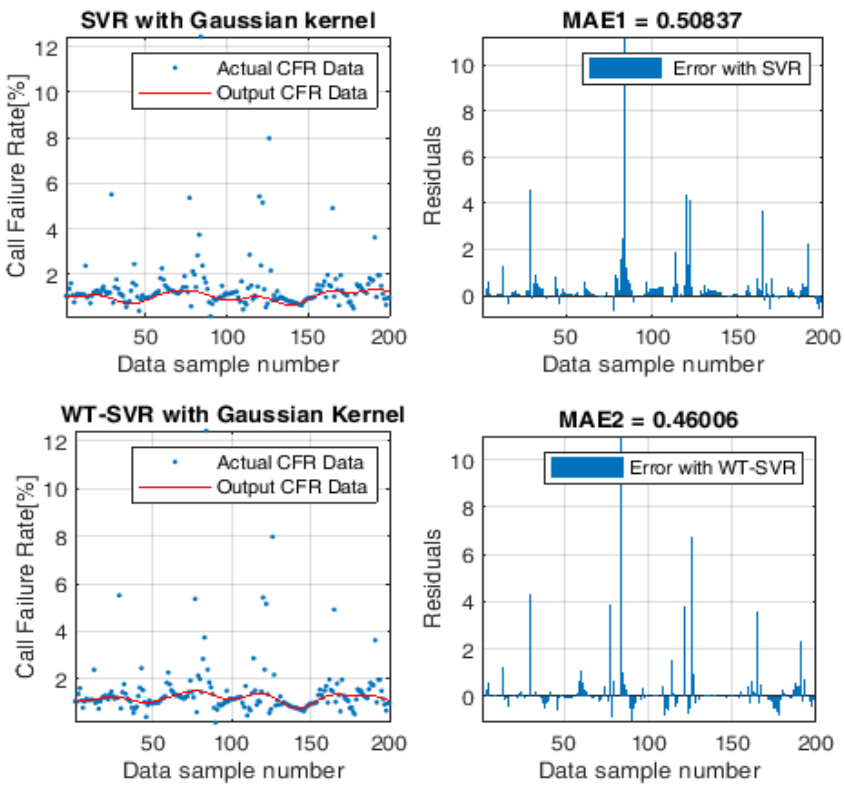


Fig.6. Adaptively learned call failure rate data with proposed WT-SVR model day 4

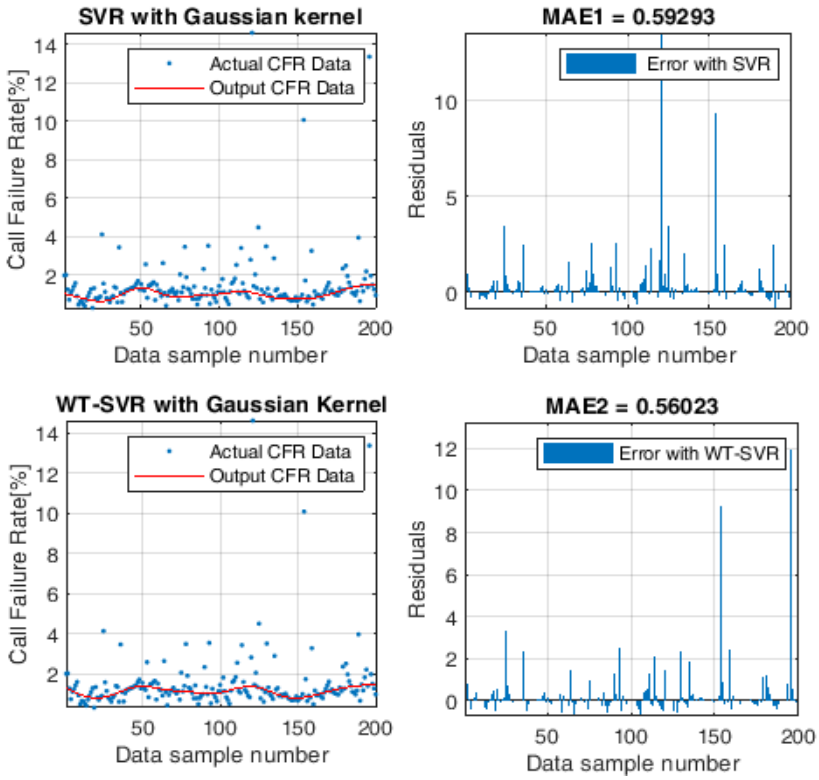


Fig. 7. Adaptively learned call failure rate data with proposed WT-SVR model day 5

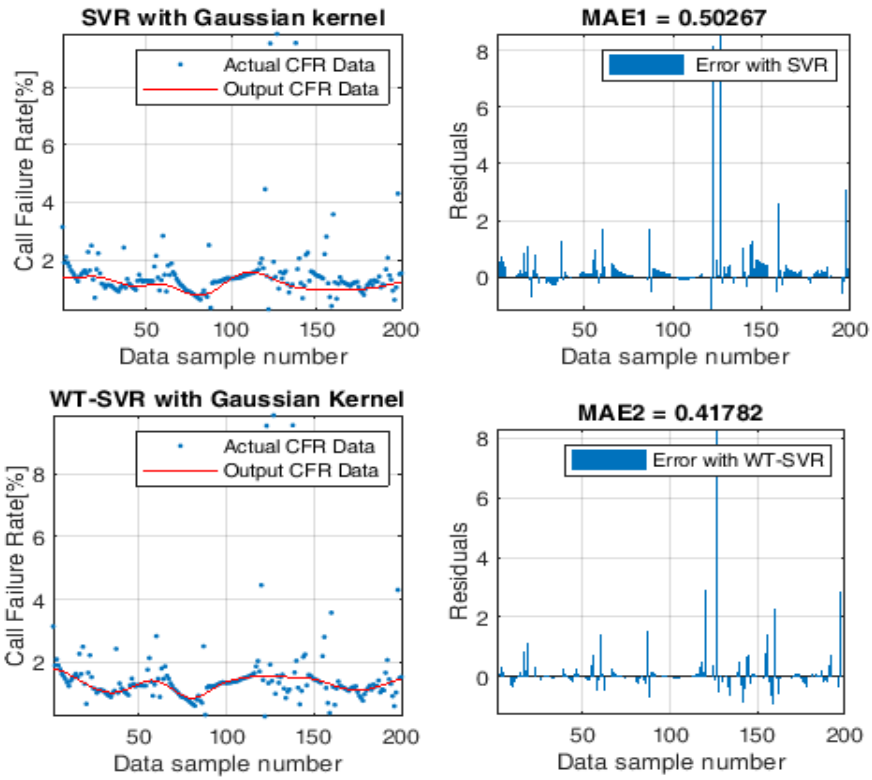


Fig.8. Adaptively learned call failure rate data with proposed WT-SVR model day 6

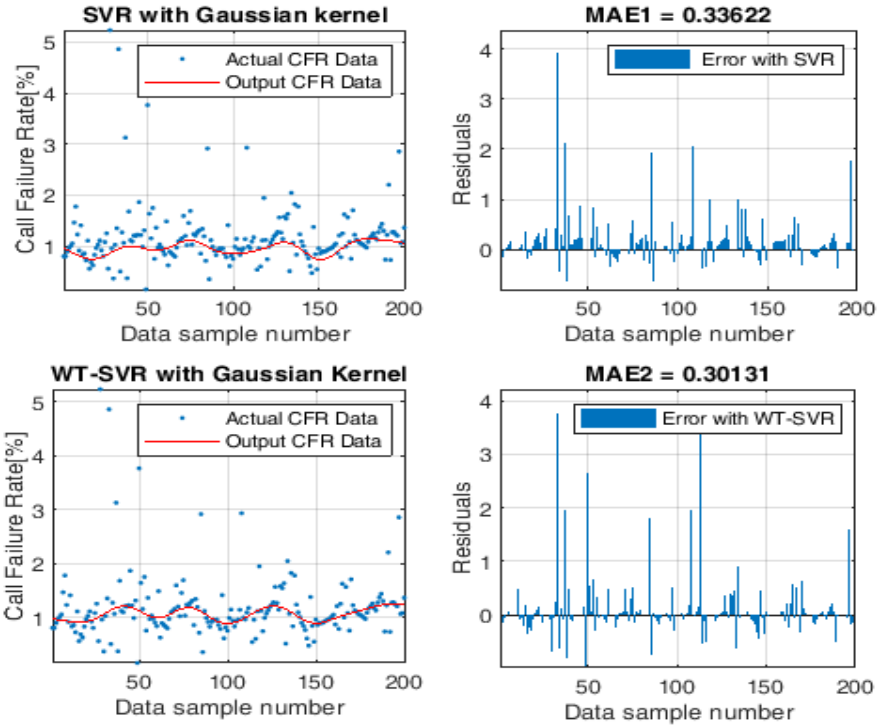


Fig. 9. Adaptively learned call failure rate data with proposed WT-SVR model day 7

Table 3. Performance of proposed WT-SVR compared to standard SVR with different kernels

Learned call failure rate with the standard SVR model for days 1 to 7														
Days	Linear					Polynomial					Gaussian			
	MAE	RMSE	PE	STD		MAE	RMSE	PE	STD		MAE	RMSE	PE	STD
1	0.70	1.15	0.35	1.10		0.69	1.17	3.52	1.34		0.45	1.14	0.38	1.08
2	0.84	2.08	0.42	2.04		0.83	2.07	0.41	2.04		0.53	2.06	0.41	2.04
3	0.63	1.08	0.59	1.03		0.63	1.07	0.31	1.04		0.28	1.03	0.29	1.02
4	0.75	1.56	0.37	1.50		0.75	1.55	0.37	1.50		0.50	1.52	0.37	1.48
5	0.80	1.84	0.40	1.78		0.79	1.84	0.33	1.78		0.59	1.82	0.38	1.77
6	0.75	1.66	0.37	1.61		0.75	1.65	0.73	1.60		0.50	1.42	0.36	1.60
7	0.52	0.89	025	0.12		0.52	0.89	0.26	0.86		0.33	0.89	0.25	0.86
Learned call failure rate with proposed WT-SVR model for days 1 to 7														
Days	Linear					Polynomial					Gaussian			
	MAE	RMSE	PE	STD		MAE	RMSE	PE	STD		MAE	RMSE	PE	STD
1	0.47	0.82	0.23	0.78		0.46	0.82	0.23	0.79		0.37	0.79	2.21	0.76
2	0.50	1.65	0.25	1.64		0.47	1.64	0.23	1.63		0.46	1.61	0.22	1.62
3	0.39	0.74	0.19	0.78		0.37	0.71	0.18	0.71		0.20	0.68	0.16	0.68
4	0.58	1.34	0.29	1.31		0.58	1.34	0.29	1.33		0.46	1.29	0.26	1.27
5	0.61	1.56	0.30	1.53		0.59	1.55	0.29	1.53		0.56	1.54	0.28	1.51
6	0.54	1.38	0.27	1.34		0.52	1.37	0.26	1.31		0.41	1.37	0.24	1.30
7	0.25	0.53	0.12	0.53		0.25	0.53	0.12	0.52		0.30	0.51	0.10	0.51

Table 4. Performance of proposed WT-SVR compared to standard SVR with different data sizes

	Linear				Polynomial				Gaussian			
Data size	MAE	RMSE	PE	STD	MAE	RMSE	PE	STD	MAE	RMSE	PE	STD
50	0.51	1.04	1.02	1.01	0.80	0.50	1.01	1.05	0.55	104	0.89	1.00
100	0.38	0.82	0.38	0.79	0.37	0.79	3.37	0.78	0.34	0.78	0.34	0.76
150	0.33	0.67	0.22	0.66	0.33	0.67	0.22	0.66	0.30	0.55	0.20	0.65
200	0.25	0.53	0.12	0.53	0.25	0.53	0.12	0.52	0.21	0.51	0.10	0.51

5. Conclusion

The call failure rate is one of the primary service quality indicators utilized to monitor the performance of wireless radio networks, and its modeling remained one of the critical components in the field of reliability engineering. This paper proposes the application of the support vector regression (SVR) method combined with wavelet transform to train

and learn the rate of call failures in wireless system networks. The wavelet transform (WT) has been accomplished using the wavelet compression sensing technique. The resultant outcome revealed that the proposed WT-SVR learning method is better than using only the SVR method for call rate prognostic analysis. Future work would focus on the optimization of the proposed WT-SVR approach for improved performance.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no conflicts of interest.

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Authors' contribution

The manuscript was written through the contributions of both authors. Conceptualization, JI; methodology, JI, and AI; writing—original draft preparation, JI; writing—review and editing, JI, and AI; supervision, JI, and AI; project administration, JI, and AI; funding acquisition, AI. All authors have read and agreed to the published version of the manuscript.

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References

[1] J. Isabona, “Parametric Maximum Likelihood Estimator combined with Bayesian and Akaike Information Criterion for Realistic Field Strength Attenuation Estimation in Open and Shadow urban Microcells,” *J. Emerg. Trends Eng. Appl. Sci.*, vol. 10, no. 4, pp. 151–156, 2019.

[2] R. Elliot, “Mobile phone penetration throughout sub-Saharan Africa.” 2020, [Online]. Available: https://www.geopoll.com/blog/mobile-phone-penetration-africa/.

[3] GSMA, “The Mobile Economy Sub-Sahara Africa 2020,” *GSMA Assoc.*, pp. 1–41, 2020, [Online]. Available: https://www.gsma.com/mobileeconomy/sub-saharan-africa/.

[4] A. Igbinovia and J. Isabona, “Empirical Investigation of Field Strength Spatial Coverage Variability in Mobile Radio Communication Networks,” *Int. J. Res. Stud. Electr. …*, vol. 4, no. 4, pp. 33–41, 2018, doi: 10.20431/2454-9436.0404004.

[5] J. Isabona and V. M. Srivastava, “User-centric methodology for objective assessment of service quality in established Wireless Mobile Communication Networks,” *Int. J. Commun. Antenna Propag.*, vol. 7, no. 1, pp. 26–30, 2017, doi: 10.15866/irecap.v7i1.10475.

[6] J. Isabona and Emughedi, O. Modelling based Quantitative Assessment of Operational LTE Mobile Broadband Networks Reliability: a Case Study of University Campus Environ**,** IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) e-ISSN: 2278-2834,p- ISSN: 2278-8735.Vol.15, Issue 1, Ser. I (Jan-Feb 2020), PP 22-31 www.iosrjournals.org

[7] A. L. Imoize, K. Orolu, and A. A.-A. Atayero, “Analysis of key performance indicators of a 4G LTE network based on experimental data obtained from a densely populated smart city,” *Data Br.*, vol. 29, no. 105304, pp. 1–17, 2020, doi: 10.1016/j.dib.2020.105304.

[8] A. L. Imoize and O. D. Adegbite, “Measurements-Based Performance Analysis of a 4G LTE Network in and Around Shopping Malls and Campus Environments in Lagos Nigeria,” *Arid Zo. J. Eng. Technol. Environ.*, vol. 14, no. 2, pp. 208–225, 2018.

[9] X. Wang, C. Yu, and Y. Li, “A New Finite Interval Lifetime Distribution Model for Fitting Bathtub-Shaped Failure Rate Curve,” *Math. Probl. Eng.*, vol. 2015, p. 954327, 2015, doi: 10.1155/2015/954327.

[10] S. J. Almalki and J. Yuan, “A new modified Weibull distribution,” *Reliab. Eng. Syst. Saf.*, vol. 111, pp. 164–170, 2013, doi: https://doi.org/10.1016/j.ress.2012.10.018.

[11] J. M. F. Carrasco, E. M. M. Ortega, and G. M. Cordeiro, “A generalized modified Weibull distribution for lifetime modeling,” *Comput. Stat. Data Anal.*, vol. 53, no. 2, pp. 450–462, 2008, doi: https://doi.org/10.1016/j.csda.2008.08.023.

[12] A. J. Lemonte, “A new exponential-type distribution with constant, decreasing, increasing, upside-down bathtub and bathtub-shaped failure rate function,” *Comput. Stat. Data Anal.*, vol. 62, pp. 149–170, 2013, doi: https://doi.org/10.1016/j.csda.2013.01.011.

[13] G. D. C. Barriga, F. Louzada-Neto, and V. G. Cancho, “The complementary exponential power lifetime model,” *Comput. Stat. Data Anal.*, vol. 55, no. 3, pp. 1250–1259, 2011, doi: https://doi.org/10.1016/j.csda.2010.09.005.

[14] G. S. Mudholkar and D. K. Srivastava, “Exponentiated Weibull family for analyzing bathtub failure-rate data,” *IEEE Trans. Reliab.*, vol. 42, no. 2, pp. 299–302, 1993, doi: 10.1109/24.229504.

[15] G. S. Mudholkar, K. O. Asubonteng, and A. D. Hutson, “Transformation of the bathtub failure rate data in reliability for using Weibull-model analysis,” *Stat. Methodol.*, vol. 6, no. 6, pp. 622–633, 2009, doi: https://doi.org/10.1016/j.stamet.2009.07.003.
[16] M. E. Ghitany, “The monotonicity of the reliability measures of the beta distribution,” *Appl. Math. Lett.*, vol. 17, no. 11, pp. 1277–1283, 2004, doi: https://doi.org/10.1016/j.aml.2003.12.007.
[17] M. Xie, Y. Tang, and T. N. Goh, “A modified Weibull extension with bathtub-shaped failure rate function,” *Reliab. Eng. Syst. Saf.*, vol. 76, no. 3, pp. 279–285, 2002, doi: https://doi.org/10.1016/S0951-8320(02)00022-4.
[18] Ivan Izonina and R. Tkachenko. An approach towards the response surface linearization via ANN-based cascade scheme for regression modeling in Healthcare, international workshop on Small and Big Data Approaches in Healthcare (SBDaH) November 1-4, 2021, Leuven, Belgium, Procedia Computer Science 198 (2022) 724–729.
[19] R. Tkachenko, I. Izonin, I. Dronyuk, M. Logoyda and P. Tkachenko , Recovery of Missing Sensor Data with GRNN-based Cascade Scheme, International Journal of Sensors, Wireless Communications and Control 2021; 11(5) . https://dx.doi.org/10.2174/2210327910999200813151904.
[20] J.Isabona *and* K Rotimi.“Multi-Resolution Based Discrete Wavelet Transform for Enhanced Signal Coverage Processing and Prediction Analysis,” *FUDMA J. Sci.*, vol. 3, no. 1, pp. 6–15, 2019.
[21] J. Cheng, D. Yu, and Y. Yang, “Application of support vector regression machines to the processing of end effects of Hilbert–Huang transform,” *Mech. Syst. Signal Process.*, vol. 21, no. 3, pp. 1197–1211, 2007, doi: https://doi.org/10.1016/j.ymssp.2005.09.005.
[22] P. A. M. B. Henrique, P. H. M. Albuquerque, S. S. D. F. Marcelino, and Y. Peng, “Portfolio selection with support vector regression: multiple kernels comparison,” *Int. J. Bus. Intell. Data Min.*, vol. 18, no. 4, pp. 395–410, 2021, doi: 10.1504/IJBIDM.2021.115476.
[23] K. Cheng and Z. Lu, “Active learning Bayesian support vector regression model for global approximation,” *Inf. Sci. (Ny).*, vol. 544, pp. 549–563, 2021, doi: https://doi.org/10.1016/j.ins.2020.08.090.
[24] L. Wu *et al.*, “Artificial Neural Network Based Path Loss Prediction for Wireless Communication Network,” *IEEE Access*, vol. 8, pp. 199523–199538, 2020, doi: 10.1109/ACCESS.2020.3035209.
[25] V. C. Ebhota, J. Isabona, and V. M. Srivastava, Environment-Adaptation Based Hybrid Neural Network Predictor for Signal Propagation Loss Prediction in Cluttered and Open Urban Microcells,” *Wirel. Pers. Commun.*, vol. 104, no. 3, pp. 935–948. doi: 10.1007/s11277-018-6061-2
[26] Joseph Isabona, Divine O. Ojuh, "Application of Levenberg-Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains", *International Journal of Intelligent Systems and Applications*, Vol.13, No.3, pp.35-42, 2021.
[27] Isabona Joseph， Divine O. Ojuh, " Adaptation of Propagation Model Parameters toward Efficient Cellular Network Planning using Robust LAD Algorithm", *International Journal of Wireless and Microwave Technologies*, Vol.10, No.5, pp. 13-24, 2020.
[28] Divine O. Ojuh, Joseph Isabona," Empirical and Statistical Determination of Optimal Distribution Model for Radio Frequency Mobile Networks Using Realistic Weekly Block Call Rates Indicator ", *International Journal of Mathematical Sciences and Computing*, Vol.7, No.3, pp. 12-23, 2021.

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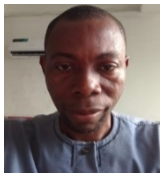

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