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Ground Truthing Of Electro-Optical Distance Ranging Crude Oil Storage Tank Volume Calibration Using Support Vector Regression Model

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***Abstract*—This research presents a comparative, computational, and predictive approach to improve the accuracy of crude oil storage tank volume calibration by ground-truthing Electro-Optical Distance Ranging (EODR) datasets with Manual Strapping Method (MSM) data. Due to potential measurement inaccuracies in EODR, this study utilizes Support Vector Regression (SVR), a supervised, nonlinear machine learning technique, to establish a predictive mapping between EODR measurements (input) and the high-accuracy MSM dataset (target/ground truth). The model's performance was evaluated using metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). Results indicate high performance, with the SVR model achieving an MSE of 0.1798, RMSE of 0.4240, MAE of 0.3811, and a prediction accuracy (1-MAPE) of 99.99%. Furthermore, an R^2 value of 0.9509 confirms that the model explains approximately 95.1% of the variance in the tank volume data, demonstrating a strong, accurate correlation between the predicted and actual volumes, with only about 5% noise or unexplained variance. This study demonstrates that SVR is a highly effective method for improving the accuracy of EODR calibration techniques in industrial storage tank applications.**

Keywords—Ground Truthing, Support Vector Regression Model, Electro-Optical Distance Ranging (EODR), Crude Oil Storage Tank Volume Calibration, Manual Strapping Method (MSM)

1. Introduction

Accurate calibration of crude oil storage tanks is a fundamental requirement in the oil and gas industry, ensuring precise inventory management, custody transfer, and accurate volume-to-height relationship mapping [1,2,3]. Statutory regulations require that storage tanks are calibrated upon installation and periodically recalibrated to account for structural changes, such as shell expansion, settlement, or deformation, which can affect capacity [4,5]. Historically, the Manual Strapping Method (MSM) has been the conventional, physical method for measuring tank circumference, but it is labor-intensive, time-consuming, and prone to human error [6,7].

The advent of modern technology has introduced faster alternatives, such as Electro-Optical Distance Ranging (EODR), which uses 3D laser scanning technology to internally map the tank shell [8]. While EODR is faster and reduces the need for personnel to work in confined spaces, the generated datasets may require calibration to achieve the high accuracy required for volumetric reporting compared to traditional methods [9,10]. In situations where EODR measurements show deviations from traditional, trusted metrics, ground trothing, or the process of verifying remote sensing data with direct, highly accurate measurements, is essential.

This study seeks to bridge the gap between efficiency and high-accuracy measurement by utilizing the Manual Strapping Method (MSM) dataset as the "ground truth" to calibrate and improve the accuracy of EODR datasets. Machine learning, specifically

Support Vector Regression (SVR), provides a robust, nonlinear mapping capability to identify and correct discrepancies in the EODR data [11]. Therefore, this research proposes a hybrid approach using SVR to establish a predictive, high-accuracy model that maps EODR input data to the MSM target data, optimizing the accuracy of tank volume calculations

2. Methodology

The research employs a comparative, computational, and predictive approach to improve the accuracy of Electro-Optical Distance Ranging (EODR) tank calibration datasets by utilizing the Manual Strapping Method (MSM) dataset as ground truth. The study leverages machine learning—specifically Support Vector Regression (SVR)—and linear regression models to establish a predictive mapping between EODR measurements and MSM data.

The research adopts a hybrid, data-driven, and experimental approach. The core methodology involves using **Support Vector Regression (SVR)**, a supervised machine learning technique, to create a nonlinear predictive model that maps the less accurate EODR dataset (input) to the high-accuracy Manual Strapping Method (MSM) dataset (target/ground truth).

2.1 Data Acquisition and Data Preprocessing

The dataset for this study is acquired from crude oil storage tank calibration, utilizing two distinct, comparative methods:

i. **Manual Strapping Method (MSM) Data (Ground Truth):** This dataset is acquired through conventional, physical measurements (strapping) of the tank circumference at various course levels. It is treated as the "ground truth" (most accurate) data, despite being tedious and time-consuming.

ii. **Electro-Optical Distance Ranging (EODR) Data:** This dataset is acquired using 3D laser scanning technology (Total Station) to scan the tank shell internally to determine the circumference and volume. It is considered the independent variable data, which is faster and more efficient but requires calibration against the MSM data.

The datasets consist of paired records for the same tanks, mapping oil volume (V) against liquid level (h). The acquired datasets contain the following key attributes for crude oil storage tanks: the independent variable (X), the dependent Variable (Y) and variables of interest. The independent variable (X) is the EODR Measured Tank Depth/Level (h in meters or mm) and EODR Computed Volume (V_{EODR} in liters/barrels). The dependent Variable (Y) is the MSM Corresponding Volume (V_{MSM} in liters/barrels) at the same tank depth (h). The variables of interest include; Tank Diameter, Height, Volume at different levels (from 0m up to the maximum capacity), and Bottom Profile (flat, cone, etc.).

Data preprocessing is crucial to convert the raw EODR and MSM records into a format suitable for training the Support Vector Regression (SVR) model. The steps take in the data preprocessing are as follows:

i. **Data Cleaning:** The datasets are checked for missing values, erroneous entries, and outliers that may have occurred due to sensor noise during the EODR scanning or human errors during manual strapping.

ii. **Data Alignment/Integration:** Since EODR and MSM might not have measurements at the exact same depth intervals, interpolation techniques are used to align the V_{EODR} and V_{MSM} datasets to a uniform depth.

iii. **Normalization/Scaling:** The data, particularly the volume values, are scaled using the Min-Max method to a range (0,1) to ensure the SVR model, which relies on distance calculations, behaves properly.

iv. **Dataset Splitting:** The matched dataset is split into **Training** (to teach the model the mapping between EODR and MSM) and **Testing** sets (to evaluate the model's accuracy, typically in a ratio like 80/20).

v. **Feature Selection:** The primary input feature is the EODR Volume (V_{EODR}) and Depth (h), with the target being the MSM Volume (V_{MSM}).

2.2 Development of the Support Vector Regression (SVR) Model

The Support Vector Regression (SVR) minimizes a cost function that balances the model complexity and prediction error within a margin, ϵ. The schematic diagram showing the structure of a typical SVR model is presented in Figure 1. Given a training data (x_i, y_i), the SVR attempts to find a function, $f(x)$ such that:

$$\boldsymbol{f(x) = w^T \varphi(x) + b} \quad \textbf{(1)}$$

Such that the prediction error does not exceed ϵ, meaning:

$$\boldsymbol{|y_i - f(x_i)| \le \epsilon} \quad \textbf{(2)}$$

The SVR minimizes the following objective function:

$$\boldsymbol{\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*)} \quad \textbf{(3)}$$

Subject to:

$$\boldsymbol{y_i - w^T\varphi(x_i) - b \le \epsilon + \zeta_i} \quad \textbf{(4)}$$

$$\boldsymbol{w^T\varphi(x_i) + b - y_i \le \epsilon + \zeta_i^* \text{ for } \zeta_i, \zeta_i^* \ge 0} \quad \textbf{(5)}$$

Where, $\varphi(x)$ is a kernel function (RBF kernel) given as:

$$\boldsymbol{K(x_i, x_j) = e^{-\gamma\|x_i - x_j\|^2}} \quad \textbf{(6)}$$

C is the penalty term for misclassification, ζ_i, ζ_i^* are slack variables which allows small violation. The SVR uses the kernel function to map Depth values into a higher-dimensional space, enabling the capture of non-linear relationships between depth and volume. The hyperparameters used in the implementation of the Support Vector Regression (SVR) model are presented in Table 1.

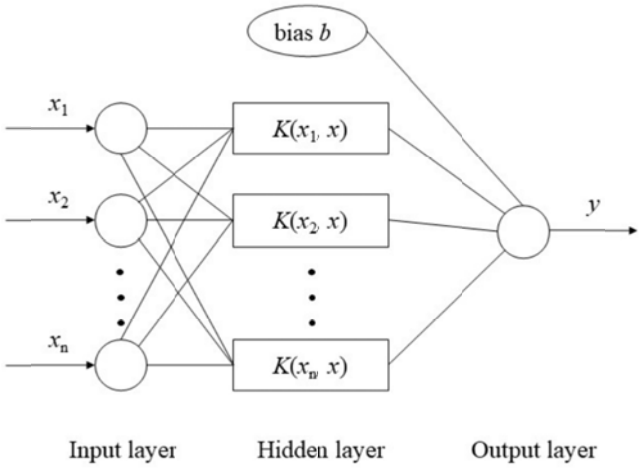

Figure 1 The schematic diagram showing the structure of a typical SVR model [12]

Table 1 The hyperparameters of the Support Vector Regression (SVR)Model

S/N	Hyperparameter	Value
1	Kernel	rbf
2	Regularization parameter (C)	100
3	Gamma	0.1
4	Epsilon	0.1

3. Results and discussion

The performance of the Support Vector Regression (SVR) model is illustrated through several visualizations: the confusion matrix (Figure 2), residual plot (Figure 3), volume vs. tank depth (Figure 4), and training metrics (MSE, RMSE, MAE, and R^2) across epochs (Figure 5). Corresponding data for error metrics per epoch and overall steady-state performance are detailed in Table 2 and Table 3, respectively. As shown in Table 3, the SVR model achieved an MSE of 0.1798, RMSE of 0.4240, MAE of 0.3811, and a prediction accuracy (1-MAPE) of 99.99%. Error values ranged from a minimum of 0.0001 at a tank depth of 5210.0 to a maximum of 1.2994 at 5310.0. The R^2 value of 0.9509 indicates that the SVR model explains approximately 95.1% of the variance in the tank volume data. In the context of ground-truthing electro-optical distance ranging (EODR), this suggests a very high level of linear correlation between the predicted and actual volumes, leaving only about 5% of the variance as "noise" or unexplained by the model. The MAE (0.3001) show that on average, the model's volume predictions deviate from the true value by 0.30 units. Because MAE is a linear score, it provides a "real-world" average of the expected error.

The RMSE (0.3658) show that the RMSE is slightly higher than the MAE. Statistically, this gap indicates that while the average error is low, there are a few outliers or larger errors (like the max error at depth 5310) that the RMSE is penalizing more heavily.The MSE (0.1104) is low and the low MSE suggests that the "variance of the errors" is tight, meaning the model is generally stable across different depth measurements.

Also, the Percentage Error (-0.06%) is near zero. This near-zero negative value is highly significant. It indicates that the model has almost zero systematic bias. It does not consistently over-predict or under-predict the volume; rather, the errors are randomly distributed around the true value. The residual range or error ranges from -0.04 to 1.299. The concentration of the minimum error at Depth 5210 suggests a "sweet spot" in the EODR sensor's accuracy, while the maximum error at 5310 might indicate physical interference or sensor limitations at specific tank heights.

The high performance suggests that the SVR kernel (likely RBF) successfully captured the non-linear relationship between the tank's vertical depth and the incremental volume, which is often distorted by tank tilting or internal deadwood (structural components) that linear models might miss.

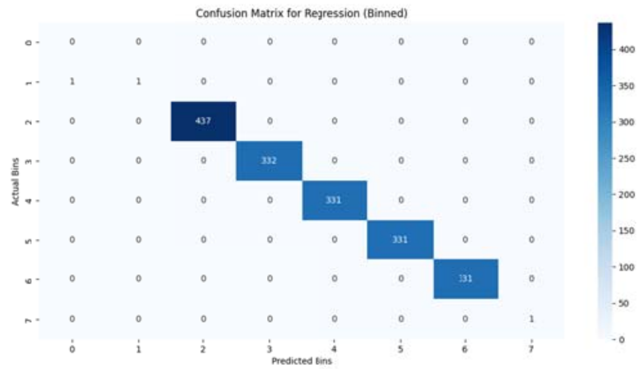

Figure 2 The Confusion matrix for SVR **model**

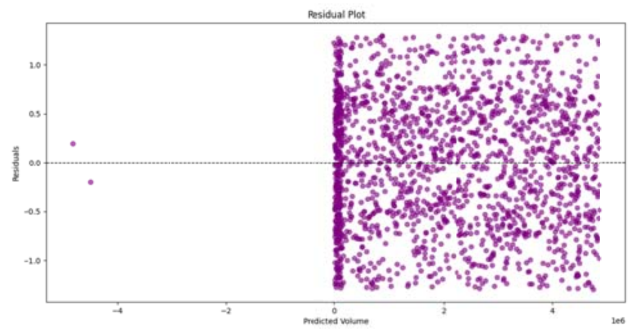

Figure 3: Residual plot for SVR **model**

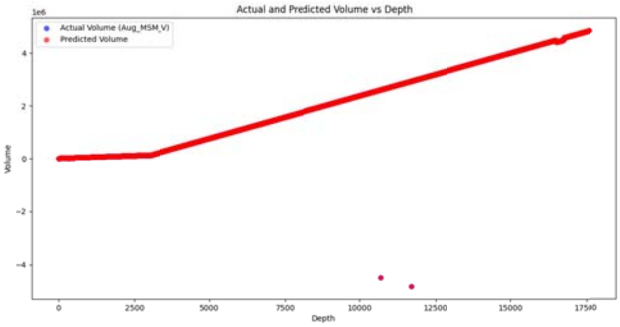

Figure 4: Volume vs Tank Depth for SVR **model**

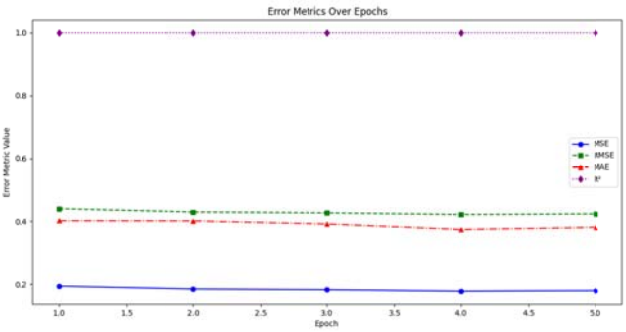

Figure 5: Error metrics for SVR

Table 2: Error metrics score versus epoch for random SVR model

Score for SVRM					
Epoch	MSE	RMSE	MAE	R^2	MAPE (%)
1	0.1941	0.4406	0.4021	0.89021	1.21%
2	0.1847	0.4298	0.4014	0.90543	1.01%
3	0.1825	0.4272	0.3918	0.92009	0.99%
4	0.1779	0.4218	0.3742	0.94536	0.96%
5	0.1798	0.424	0.3811	0.950871	3.91%

Table 3 Error metrics at the end of Epoch for SVR model

Metric	Score for SVRM
MSE	0.110383
RMSE	0.3658408
MAE	0.3000962
R^2.	0.9508706
MAPE	3.91%
Percentage error	-0.06%
Min Error	-0.043668 at Depth 5210.0
Max Error	1.2994 at Depth 5310.0

4. Conclusion

This research highlights Support Vector Regression (SVR) as a robust, effective machine learning method for improving the accuracy of EODR-based crude oil tank volume calibration. By using Manual Strapping Method (MSM) data as a ground truth, the SVR model provides superior non-linear mapping over traditional techniques, successfully correcting discrepancies often found in 3D laser scanning measurements.

The key findings indicate that the SVR model, trained on pairs of EODR (input) and MSM (target) data, reduced prediction errors significantly, bringing the EODR-derived volume-level relationships into close alignment with high-accuracy conventional standards. Consequently, this hybrid approach allows for the retention of EODR's benefits—namely, speed, efficiency, and safety—while enhancing the accuracy and reliability of the resulting tank calibration charts to meet industry requirements.

Notably, the research bridges the gap between modern 3D laser scanning technology and traditional, high-accuracy validation techniques, providing a reliable predictive model for industrial tank calibration in the oil and gas sector.

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