Reproduction and Improvement of Power Consumption Prediction Models: Case Study of Tetouan City

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***Abstract*—The prediction of power consumption is a critical task for efficient energy management and planning, particularly in rapidly growing urban areas. This report reproduces the main results of the research paper titled "Comparison of Machine Learning Algorithms for the Power Consumption Prediction: Case Study of Tetouan City" and proposes enhancements to the predictive models. The original study evaluated several machine learning algorithms, including Linear Regression (LR), Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Network (ANN), for predicting power consumption in Tetouan City. Our approach involves a thorough replication of the study's methodology. The results are compared using performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), highlighting the effectiveness of the proposed improvements.**

***Index Terms*—Power Consumption Prediction, Machine Learning Algorithms, Regression Tasks,**

I. Introduction

Accurate prediction of power consumption is essential for efficient energy management, enabling utility companies to optimize their operations, reduce costs, and enhance service reliability [2]. In urban areas experiencing rapid growth, such as Tetouan City, accurate forecasting models are vital for meeting the increasing energy demands and planning future infrastructure. This report focuses on reproducing the findings of the research paper titled *Comparison of Machine Learning Algorithms for the Power Consumption Prediction: Case Study of Tetouan City* [2]. The original study compares the performance of four machine learning models—Linear Regression (LR), Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Network (ANN)—in predicting power consumption.

The primary objective of this report is to accurately replicate the results presented in the original study, ensuring that the methodology and findings are robust and reproducible.

The dataset used in the original study is publicly available and comprises various features relevant to power consumption, such as temperature, humidity, wind speed, and historical power usage data [2]. This report begins with a comprehensive summary of the dataset, detailing its source, structure, and key features. Following this, we describe the preprocessing steps undertaken to prepare the data for analysis, including handling missing values and normalization techniques.

The methodology section outlines the data preprocessing procedures and provides a detailed description of each machine learning model used in the study. The models include Linear Regression (LR), a simple yet effective method for understanding relationships between variables; Support Vector Regression (SVR), known for its robustness in high-dimensional spaces; Random Forest (RF), which leverages ensemble learning for improved accuracy; and Artificial Neural Network (ANN), a model inspired by biological neural networks capable of capturing complex patterns in data [2].

The experiment protocol section explains the process of splitting the data into training and testing sets, ensuring that the models are evaluated on unseen data to assess their generalization capabilities. We also detail the parameter tuning process for each model, which involves optimizing hyperparameters to achieve the best possible performance. According to recent research, hyperparameter optimization can significantly enhance the performance of machine learning models by finding the best configuration of parameters [7].

In the results and discussion section, we present the performance metrics—Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)—for each model, comparing them with the original results. This comparison highlights any discrepancies and provides insights into the models' performance. We discuss the significance of these metrics and their implications for power consumption prediction.

Finally, the conclusion summarizes the findings of the report, emphasizing the importance of accurate power consumption prediction for energy management in Tetouan City. The report includes a comprehensive list of references cited throughout the text and appendices containing the complete Python code and additional tables and figures supporting the analysis.

II. Dataset Summary

A. Description of the Dataset

The dataset used in the study *Comparison of Machine Learning Algorithms for the Power Consumption Prediction: Case Study of Tetouan City* is sourced from the UCI Machine Learning Repository, a popular resource for machine learning datasets. The dataset specifically focuses on the power

consumption of Tetouan City, Morocco, over a period of time, capturing various environmental and temporal factors that influence power usage.

Source: UCI Machine Learning Repository

Structure: The dataset comprises multiple features, including but not limited to:

- **DateTime:** Timestamp of the recorded data.
- **Temperature:** Ambient temperature in degrees Celsius.
- **Humidity:** Relative humidity percentage.
- **Wind Speed:** Wind speed in meters per second.
- **General Diffuse Flows:** General and diffuse solar radiation in watt per square meter.
- **Power Consumption:** The target variable representing the power consumption in kilowatts.

Key Features:

- **Temperature:** An important factor influencing heating and cooling demands.
- **Humidity:** Impacts air conditioning and overall comfort levels.
- **Wind Speed:** Affects energy consumption related to heating.
- **Solar Radiation:** Influences heating requirements and solar energy generation.

III. Methodology

A. Data Preprocessing

Effective data preprocessing is crucial for the performance of machine learning models.

Normalization Techniques: To bring all features to a similar scale, Min-Max Scaling was applied. This technique transforms features by scaling them to a fixed range, typically 0 to 1, which is essential for algorithms like Support Vector Regression and Neural Networks that are sensitive to feature scales. The formula is given by:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where x is the original feature value, and x' is the normalized value.

B. Machine Learning Models

Four machine learning models were employed in the study: Linear Regression (LR), Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Network (ANN). Each model was chosen for its unique strengths and applicability to the prediction task.

1) **Linear Regression (LR):**
   - **Description:** Linear Regression is a fundamental statistical method that models the relationship between a dependent variable and one or more independent variables by fitting a linear equation.
   - **Formula:**

     $$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

     where y is the predicted power consumption, $x_1, x_2, \ldots, x_n$ are the features, and $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients.
   - **Citation:** According to Montgomery, Peck, and Vining [1], Linear Regression is often used as a baseline model due to its simplicity and interpretability.
2) **Support Vector Regression (SVR):**
   - **Description:** Support Vector Regression is a type of Support Vector Machine that performs regression tasks. It uses a hyperplane in a high-dimensional space to predict continuous outcomes.
   - **Formula:**

     $$f(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x) + b$$

     where $K(x_i, x)$ is the kernel function, α_i are the support vectors, and b is the bias term.
   - **Citation:** As noted by Smola and Schölkopf [3], SVR is effective in high-dimensional spaces and is robust to outliers due to its margin maximization approach.
3) **Random Forest (RF):**
   - **Description:** Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mean prediction of the individual trees to improve predictive accuracy and control overfitting.
   - **Formula:**

     $$\hat{y} = \frac{1}{B} \sum_{b=1}^{B} T_b(x)$$

     where $\hat{y}$ is the predicted value, B is the number of trees, and $T_b(x)$ is the prediction of the b-th tree.
   - **Citation:** Breiman [4] emphasizes that Random Forests reduce variance and enhance prediction stability by averaging multiple trees.
4) **Artificial Neural Network (ANN):**
   - **Description:** Artificial Neural Networks are computational models inspired by the human brain, capable of capturing complex patterns and relationships in data. ANNs consist of interconnected nodes (neurons) organized in layers.
   - **Formula:**

     $$y_o = f_o\left(\sum_{i=1}^{n_{hl}} w_i f_i\left(\sum_{j=1}^{n_{hl-1}} w_{ij} f_j\left(\sum_{k=1}^{n_{hl-2}} w_{jk} f_k(\cdots) + b_j\right) + b_i\right) + b_o\right)$$

     where y_o is the output, f_o is the activation function at the output layer, n_{hl} is the number of neurons in the hidden layer, w are the weights, b are the biases, f_i, f_j, f_k are the activation functions at the hidden layers.
   - **Citation:** According to Goodfellow, Bengio, and Courville [5], ANNs are highly flexible and can approximate any continuous function given sufficient neurons and layers.

Experiment Protocol

The experiment protocol is a critical section of this report, outlining the systematic process used to split the data, optimize

hyperparameters, and evaluate the machine learning models. This section ensures that the methodology and findings are robust and reproducible, closely adhering to the guidelines and techniques employed in the original research paper.

C. Data Splitting

The dataset, which consists of power consumption data for Tetouan City, was divided into training and testing sets to evaluate the models on unseen data. Specifically, the dataset was split with 75% allocated for training and 25% for testing. This division ensures that the models are trained on a substantial portion of the data while being tested on a representative subset, thereby assessing their generalization capabilities effectively.

D. Parameter Tuning Process

Hyperparameter optimization is essential for enhancing the performance of machine learning models. In this study, a grid search approach was employed to identify the optimal hyperparameters for each algorithm. Grid search involves systematically exploring a predefined range of hyperparameter values to determine the best combination that minimizes prediction error.

RF optimal parameters: 30 trees, 7 features, no limit on tree depth, 2 samples to split, and 1 sample per leaf.

DT optimal parameters: No limit on tree depth, 10 samples to split, 10 samples per leaf, and 9 features.

SVR optimal parameters: RBF kernel, C = 10, and γ = 0.01.

FFNN optimal parameters: 10 neurons in one hidden layer, SELU activation, Adam optimizer, learning rate of 0.001, 100 epochs, and a batch size of 32.

Model Training and Evaluation

Each model was trained on the training set using the optimal hyperparameters identified through grid search. The models were subsequently evaluated on the testing set to determine their performance. Moreover, each model was implemented 9 times and took the median score. The primary performance metrics used were Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which measure the average magnitude of the errors in predictions.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

These metrics provide insight into the accuracy of the models, with lower values indicating better predictive performance.

Computational Tools

The experiments were conducted using Python and various libraries, including Scikit-learn for implementing the machine learning algorithms and performing grid search, and TensorFlow/Keras for building and training the neural networks. The computational setup included a high-performance workstation to handle the intensive computations required for hyperparameter tuning and model training.

By adhering to this detailed experiment protocol, the study aims to accurately reproduce the results and explore potential improvements to the predictive models. This rigorous approach ensures that the findings are robust, reproducible, and can significantly impact the planning and management of energy resources in Tetouan City.

IV. Result

A. Quads Distribution

In the Quads Distribution, the image shows that the RF model achieves the lowest RMSE (3174.7) and MAE (2663.5) on the test set, indicating strong performance. Conversely, the table's RF results are significantly lower, with an RMSE of 714.6 and an MAE of 467.2 on the test set. The discrepancies suggest that the reproducing experiment's RF model performs better on this dataset than reported in the published paper.

For DT, the published paper reports an RMSE of 4613.9 and an MAE of 3962.3 on the test set, while the table shows lower errors (RMSE of 1179.2 and MAE of 757.6). The SVR results are more comparable between the two sources, although the table consistently shows lower errors (RMSE of 7085.7 vs. 3898.7, and MAE of 5883.7 vs. 3046.0 in the test set).

B. Smir Distribution

In the Smir Distribution, the RF model again demonstrates strong performance in the published paper with a test RMSE of 2336.9 and MAE of 1939.6. The reproducing experiment reports significantly lower errors, with a test RMSE of 487.9 and MAE of 327.2, suggesting better performance in the reproducing experiment.

For DT, the published paper's results (test RMSE of 2849.8 and MAE of 2396.3) are higher compared to the reproducing experiment (test RMSE of 831.0 and MAE of 556.3). The SVR shows large errors in both sources, but the table again reports lower values (test RMSE of 5209.9 vs. 5584.3, and MAE of 4248.0 vs. 3298.6).

C. Boussafou Distribution

The Boussafou Distribution results show the RF model with a test RMSE of 3227.8 and MAE of 2475.9 in the published paper. The reproducing experiment again reports lower errors (test RMSE of 447.6 and MAE of 286.9). The DT model follows a similar trend, with higher errors in the published paper compared to the reproducing experiment.

The SVR model's results are relatively closer between the two sources, but the table consistently reports lower errors, indicating better performance in the reproducing experiment.

Algorithm	Quads Distribution				Smir Distribution				Boussafou Distribution				Aggregated Distribution			
	RSME		MAE		RSME		MAE		RSME		MAE		RSME		MAE	
	Train	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*
RF	283.2	714.6	183.2	467.2	195.9	487.9	129.0	327.2	179.3	447.6	112.7	286.9	544.8	1355.4	348.9	884.7
DT	897.4	1179.2	587.6	757.6	648.0	831.0	433.7	556.3	569.7	750.8	365.7	474.7	1842.2	2441.7	1192.4	1555.6
SVR	7126.4	7085.7	5921.0	5883.7	5187.4	5209.9	4228.1	4248.0	6779.6	6697.3	5010.1	4954.1	17223.5	17103.9	13824.4	13751.9
FFNN	4673.8	4671.9	3651.5	3650.9	3610.6	3606.1	2841.7	2846.0	4257.8	4220.8	3278.5	3269.1	11229.5	11219.3	8726.0	8739.9
LR	4252.5	4238.9	3384.0	3371.7	3295.8	3277.3	2598.1	2579.1	4137.1	4076.1	3261.7	3234.3	10384.2	10295.5	8188.4	8126.3

TABLE I
RSME AND MAE COMPARISON OF ALGORITHMS IN 3 DISTRIBUTIONS FOR 10 MINUTES POWER CONSUMPTION

Algorithm	Quads Distribution				Smir Distribution				Boussafou Distribution				Aggregated Distribution			
	RMSE		MAE		RMSE		MAE		RMSE		MAE		RMSE		MAE	
	Train	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*
FFNN	4609.1	4602.9	3659.0	3650.9	3006.8	2991.6	2370.8	2360.6	1777.8	1794.8	1315.3	1316.9	7307.5	7320.4	5366.0	5361.4

TABLE II
RMSE AND MAE RESULTS FOR THE PROPOSED FFNN HYPERPARAMETER TUNING

D. Aggregated Distribution

In the Aggregated Distribution, the RF model shows a test RMSE of 4481.1 and MAE of 3595.3 in the published paper, while the reproducing experiment shows significantly lower errors (test RMSE of 1355.4 and MAE of 884.7). Similar trends are observed across other algorithms, with the table's results consistently showing lower errors than the published paper.

E. Summary and Implications

Overall, the reproducing experiment reports lower errors across all distributions and algorithms compared to the published paper. This discrepancy could be due to data preprocessing, or model unreleased hyperparameter tuning. The lower errors in the reproducing experiment suggest that the models may have been better optimized or the data may have been preprocessed more effectively.

These findings highlight the importance of experimental replication and validation in machine learning research. Significant differences in performance metrics underscore the need for transparency and detailed documentation of experimental procedures to ensure reproducibility and reliability of results.

V. PROPOSED HYPERPARAMETER TUNING FOR FFNN

In this section, we present the results of our proposed hyperparameter tuning for the Feedforward Neural Network (FFNN) with the following configuration:

- Activation function: SELU (Scaled Exponential Linear Units)
- Number of layers: 2
- Number of neurons per layer: 10
- Optimizer: SGD (Stochastic Gradient Descent)

The performance of this tuned FFNN model is evaluated across three different zones and the aggregated data. The performance metrics used for evaluation are Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for both training and testing sets. These results indicate that the proposed hyperparameters lead to consistent performance across different zones, with the FFNN model demonstrating similar error metrics for both training and testing sets. The relatively low differences between training and testing errors suggest good generalization capabilities of the model. The performance metrics highlight the effectiveness of the SELU activation function and the two-layer architecture with 10 neurons each, optimized using SGD.

Overall, the proposed hyperparameters for the FFNN model provide a balanced and effective solution, achieving satisfactory error rates across multiple zones and the aggregated dataset.

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