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VoltaResBot: A Machine Learning Model for Optimal Energy Management in Multi-Component Robotic Systems Integrated with Photovoltaics, and Storages

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***Abstract*—Predictive energy management models considerably advance financial and environmental analyses of industrial robotic manipulator energy consumption. As industries increasingly prioritize sustainability and cost-effectiveness, optimizing energy utilization becomes crucial. Consequently, this paper presents VoltaResBot, a machine learning-driven predictive techno-economic model for optimal energy management in multi-component robotic systems integrated with photovoltaics (PVs), electricity grid, and storage (ESS). VoltaResBot utilizes Support Vector Machines (SVM) to predict and optimize energy consumption, facilitating precise control of a 6 Degrees of Freedom (6 DoF) robotic manipulator. The findings of VoltaResBot indicate its effectiveness in achieving optimal energy utilization, significantly reducing environmental. Key Performance Indicators (KPIs) employed in the evaluation include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R-squared (R^2), presenting the model's accuracy. Comparative analyses with traditional machine learning models further demonstrate the superior performance of VoltaResBot.**

Keywords–*Predictive Energy Management; Techno-Economic Model; Industrial Robotic Manipulators; Energy Consumption Optimization; Machine Learning; Electricity Grid Integration*

I. Introduction

Predictive models are considered significant players in managing the energy consumption of robotic industrial manipulators, providing sustainability and cost-effectiveness. As industrial processes become increasingly reliant on advanced robotic systems, the need for precise and accurate predictions of energy needs has become significant. The presented work in [1] discusses the importance of energy efficiency in robotic manipulators, incredibly lightweight industrial robots. It introduces a pipeline to analyze energy usage in mechatronic devices, revealing that electronic components consume 60-90% of energy. Using four manipulators, the study suggests a shift towards efficient robot electronic design rather than mass distribution or motion control. The proposed disaggregation pipeline aids in optimizing power consumption in mechatronic devices.

The purpose of [2] is to optimize industrial robot control strategies for energy efficiency. Comparing a classical PID controller and a linear MPC controller on a 5-DOF Mitsubishi robot arm, the study found the MPC controller consistently executed trajectories faster with lower energy consumption. Despite the PID's precision, it incurred higher energy costs. This research underscores the potential for enhancing energy efficiency in industrial robotic systems through strategic controller selection.

The work done in [3] presents a methodology for Energy-Efficient, High-Quality Part Placement (EEHQPP) in robotic additive manufacturing. An energy-quality map guides decision-making by characterizing energy and quality variations across the robot's workspace.

A control scheme is presented by [4] for the path-following task by the end-effector of an aerial mobile manipulator robot, prioritizing energy consumption. The controller, designed based on system kinematics and considering high redundancy, allows for two objectives: precise path-following at variable speeds and energy savings by modifying the internal structure. The research [5] indicates a motion planning approach for industrial robots, utilizing the flight cost-based RRT algorithm. In [6], the Gryphon industrial robot uses a multi-rate adaptive inverse dynamic controller for stability and reliable trajectory tracking. The controller optimizes sampling periods and refresh rates, ensuring precision and stability in real-world scenarios.

Finally, the research performed in [7], is a data-driven method for predicting and optimizing industrial robot energy consumption using a deep neural network and adaptive genetic algorithm. Experimental results show accurate prediction and a substantial reduction in EC.

The development of VoltaResBot is motivated by the imperative to address the dynamic energy challenges faced by modern robotic manipulators, aiming to fill existing gaps in precision and accuracy within predictive energy management models. Recent advances in the field, particularly integrating machine learning techniques like Support Vector Machines (SVM), have paved the way for more sophisticated energy management solutions. However, the precision and accuracy of these models still present challenges. VoltaResBot is a comprehensive solution that uses SVM and advanced machine learning approaches to optimize energy consumption in multi-component robotic systems. This paper provides an overview of VoltaResBot's results, demonstrating its effectiveness in accurate predictions and energy utilization optimization. The structure of the paper includes a detailed exposition of VoltaResBot's model structure and framework in Section 2, a thorough examination of derived results and a comparative analysis in Section 3, and conclusions in Section 4.

II. Model Structure and Framework

In the energy management process, the generated power from photovoltaic sources and the absorbed energy from the grid are efficiently channeled into an electrical storage system, as conceptualized in Fig. 1. Based on Fig. 1, the integration of this dynamic energy ecosystem is overseen by VoltaResMan, leveraging an SVM model for precise control and optimization. The primary focus is meeting the energy demands of the 6 DoF robotic manipulator, aligning power supply with its load.

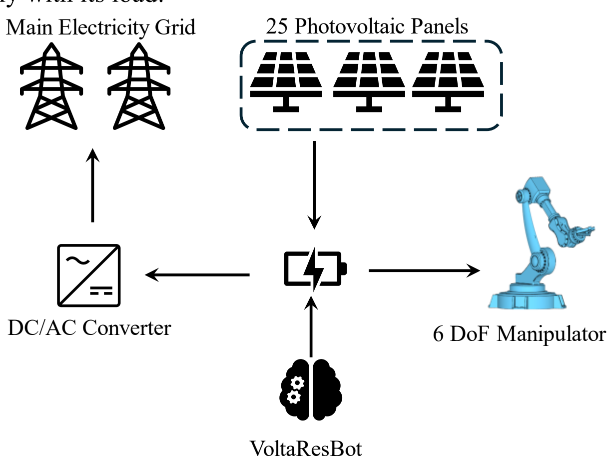


Fig. 1. The overall process of the system

An intelligent controller intricately regulates the power distribution, prioritizing energy from photovoltaics. When the photovoltaic power is insufficient to meet the robotic energy requirements, the controller seamlessly supplements it with grid energy. When photovoltaic power surpasses the manipulator's needs, excess is injected into the main grid. This strategic surplus results in a potential financial profit and contributes significantly to lowering greenhouse gas emissions, marking a considerable step towards a more sustainable and economically viable energy ecosystem. The manipulator utilized in this system is illustrated in Fig. 2.

As clarified in Fig. 2, the proposed robotic manipulator is a highly adaptable mechanical system, boasting six distinct movements encompassing translation along the X, Y, and Z axes and rotation in pitch, yaw, and roll. This intricate design enables precise positioning and orientation in three-dimensional space, facilitating a broad spectrum of tasks with remarkable accuracy. The coordination of the 6 DoF robotic manipulator is finely tuned through advanced control algorithms, exemplified by VoltaResMan, ensuring synchronized movements of its joints and actuators.

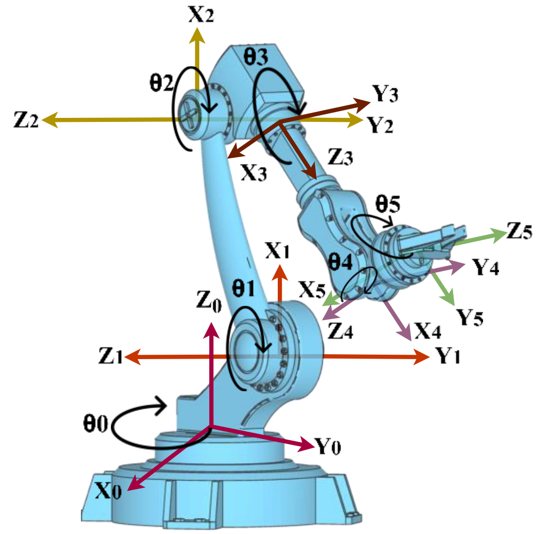


Fig. 2. Manipulator structure with its coordination

This harmonious coordination not only optimizes the manipulator's performance but also seamlessly integrates it into the broader energy system, where it efficiently utilizes energy resources and adapts to varying loads for enhanced operational efficiency, as modulated [8]:

$$\wp = \begin{bmatrix} T_1 & T_2 & T_3 \\ T_4 & T_5 & T_6 \end{bmatrix} \tag{1}$$

$$T_1 = \begin{bmatrix} C_1 & 0 & S_1 & 0 \\ S_1 & 0 & -C_1 & 0 \\ 0 & 1 & 0 & 627 \\ 0 & 0 & 0 & 1 \end{bmatrix}, T_2 = \begin{bmatrix} C_2 & -S_2 & 0 & 800C_2 \\ S_2 & C_2 & 0 & 800S_2 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$
$$T_3 = \begin{bmatrix} C_3 & 0 & S_3 & 575C_3 \\ S_3 & 0 & -C_3 & 575S_3 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}, T_4 = \begin{bmatrix} C_4 & 0 & -S_4 & 0 \\ S_4 & 0 & C_4 & 0 \\ 0 & 1 & 0 & 370 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$
$$T_5 = \begin{bmatrix} C_5 & 0 & S_5 & 140C_5 \\ S_5 & 0 & -C_5 & 140S_5 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, T_6 = \begin{bmatrix} C_6 & -S_6 & 0 & 0 \\ S_6 & C_6 & 0 & 0 \\ 0 & 0 & 1 & 70 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where T_i indicates the transformation matrix of the manipulator in each joint. As well, C_i, and S_i present the $Cos(\theta_i)$, as well as $Sin(\theta_i)$, in each joint of the robot, respectively. For the side of the controller, VoltaResBot is conceptualized as in Fig. 3.

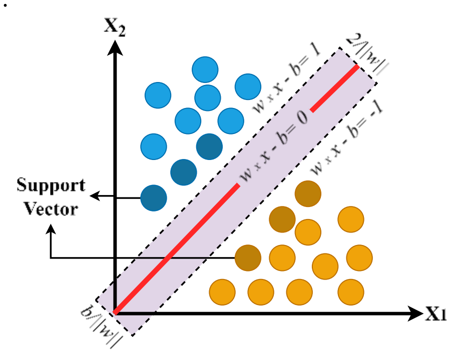


Fig. 3. The SVM concept utilized in VoltaResBot

Depending on Fig. 3, SVMs employed in VoltaResBot serve as a tool for predicting and optimizing the system's energy consumption. SVM is a supervised machine learning algorithm that excels in classification and regression tasks. SVM works by finding a hyperplane that best separates data points in the feature space to minimize prediction errors. VoltaResBot utilizes SVM to establish a robust relationship between input features such as grid power, PV, SoC, and the manipulator's energy consumption. Through the training process, the SVM model learns to generalize patterns in the data, enabling accurate predictions during system operation, modeled as:

$$f(x) = sign(w \cdot x + b) \tag{3}$$

$$O.F = min_{w,b} \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{N} \xi_i \tag{4}$$

$$s.t{:}\begin{cases} y_i(w \cdot x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \tag{5}$$

$$O.F = min_{w,b} \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{N} [\max(0, | y_i - (w \cdot x_i + b) | - \varepsilon)]^2 \tag{6}$$

where $f(x)$, w, b, and ξ are the decision function, weight vector, bias vector, as well as the misclassification slack variables, respectively. Target value, intensive loss and regularization parameters are defined by y_i, ε, also, C, respectively. As VoltaResMan imputes the electrical storage, it follows the following formulations:

$$\zeta_T = \sum_{i=0}^{N} \zeta_{Grid}[i] \cdot E_{Grid}[i] \tag{7}$$

$s.t$:

$$E_{ESS}[i] = E_{ESS}[i-1] + P_{ESS}[i]\Delta T \tag{8}$$

$$P_{PV}[i] + P_{Grid}[i] + P_{ESS}[i] = P_{Load}[i] \tag{9}$$

$$P_{PV} = \frac{A \cdot H}{\Delta T} \cdot \eta \cdot \left(\frac{X}{R}\right) \tag{10}$$

where, $\zeta_{T,}\zeta_T$, ζ_{Grid}, and E_{Grid} are the total cost, cost, and energy fed/drawn of the grid, respectively. Energy and power of storage are denoted by E_{ESS}, and P_{ESS}. P_{PV}, P_{Grid}, and P_{Load} are the power of PVs, main grid, and the load, respectively. As well, noting to ESS, its constraints are detailed as [9]:

$$0 \leq P_{ESS}^{Ch,t,\omega} \leq \frac{P_{ESS}^{Max}}{\eta_{ESS}^{Ch}} \tag{11}$$

$$0 \leq P_{ESS}^{Dch,t,\omega} \leq P_{ESS}^{Max} \eta_{ESS}^{Dch} \tag{12}$$

$$SoC_{ESS}^{t,\omega} = SoC_{ESS}^{t-1,\omega} - \frac{1}{E_{ESS}^{Max}} \left(\frac{P_{ESS}^{Dch,t,\omega}}{\eta_{ESS}^{Dch}} - \eta_{ESS}^{Ch} \cdot P_{ESS}^{Ch,t,\omega} \right) \tag{13}$$

$$0 \leq SoC_{ESS}^{t,\omega} \leq 1 \tag{14}$$

$$SoC_{ESS}^{t_0} = SoC_{ESS}^{t_{initial}} \tag{15}$$

$$SoC_{ESS}^{t_{final}} = SoC_{ESS}^{Final} \tag{16}$$

$$P_{ESS} = P_{ESS}^{Ch,t,\omega} - P_{ESS}^{Dch,t,\omega} \tag{17}$$

$$\zeta_{ESS}^{t,\omega} = A_{ESS} \cdot \left[P_{ESS}^{Ch,t,\omega} + P_{ESS}^{Dch,t,\omega} \right] \tag{18}$$

where charging power, along with maximum charging power, and efficiency of storage are symbolized by $P_{ESS}^{Ch,t,\omega}$, P_{ESS}^{Max}, and η_{ESS}^{Ch}, respectively. $P_{ESS}^{Dch,t,\omega}$, P_{ESS}^{Max}, and η_{ESS}^{Dch} are identical concepts for the discharging phase. $SoC_{ESS}^{t,\omega}$, $SoC_{ESS}^{t_{initial}}$, and SoC_{ESS}^{Final} are the SoC of the current, initial, and final phases, respectively. Thus, the ESS total cost, as well as its degradation cost are presented by $\zeta_{ESS}^{t,\omega}$, and A_{ESS}.

Finally, the model's performance is evaluated using key metrics like MAE, RMSE, MSE, and R^2, which measure the average absolute difference between predicted and actual values, sensitivity to outliers, and explanatory power. The mentioned KPIs are defined as [10-11]:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \ell_{i,actual} - \ell_{i,predicted} \tag{19}$$

$$MSE = \frac{1}{n} \sum (\ell_{actual} - \ell_{Predicted})^2 \tag{20}$$

$$RMSE = \sqrt{\frac{1}{n} \sum (\ell_{actual} - \ell_{Predicted})^2} \tag{21}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(\ell_{i,predicted} - \ell_{i,actual}\right)^2}{\sum_{i=1}^{n} \left(\ell_{i,actual} - \overline{\ell}_i\right)^2} \tag{22}$$

where n is the number of data, and $\ell_{Observed}$, with $\ell_{Predicted}$ are the observed, and predicted values of grid community, respectively.

III. Simulations and Comparative Analysis

Simulations in MATLAB and Python evaluated VoltaResBot's performance across system components (Fig. 1). Parameters like Grid [kW], SoC [%], PV [kW], and Robotic Consumption [kW] were characterized by mean and variance. Notably, for the grid, the mean was -0.024 with a variance of 0.301; SoC [%] had a mean of 50.36 and a variance of 382.54. PV [kW] showed a mean of 0.64 with a variance of 1.24, and Robotic Consumption [kW] had a mean of 0.61 with a variance of 0.19. With 1488 data points, VoltaResBot's application allowed a comprehensive assessment of its predictive accuracy and optimization capabilities within the intricate energy system dynamics, as the results are presented in Figs. 4 and 5 and Table. 1.

Based on Fig. 4, the integrated system under consideration provides diverse energy dynamics, with parameters spanning a range of values. The manipulator consumption fluctuates between 0 and 2 kW, capturing the varying power requirements of the manipulator during operation. The Grid consumption ranges from -4 to 2 kW, encompassing both energy drawn/injection scenarios. PV generate energy from 0 to 5 kW, reflecting the dynamic nature of solar power generation. The SoC varies from 20% to 80%, indicating the charging/discharging states of the storage system. Additionally, Greenhouse gas emissions, span from 0 to 200 g/sec.

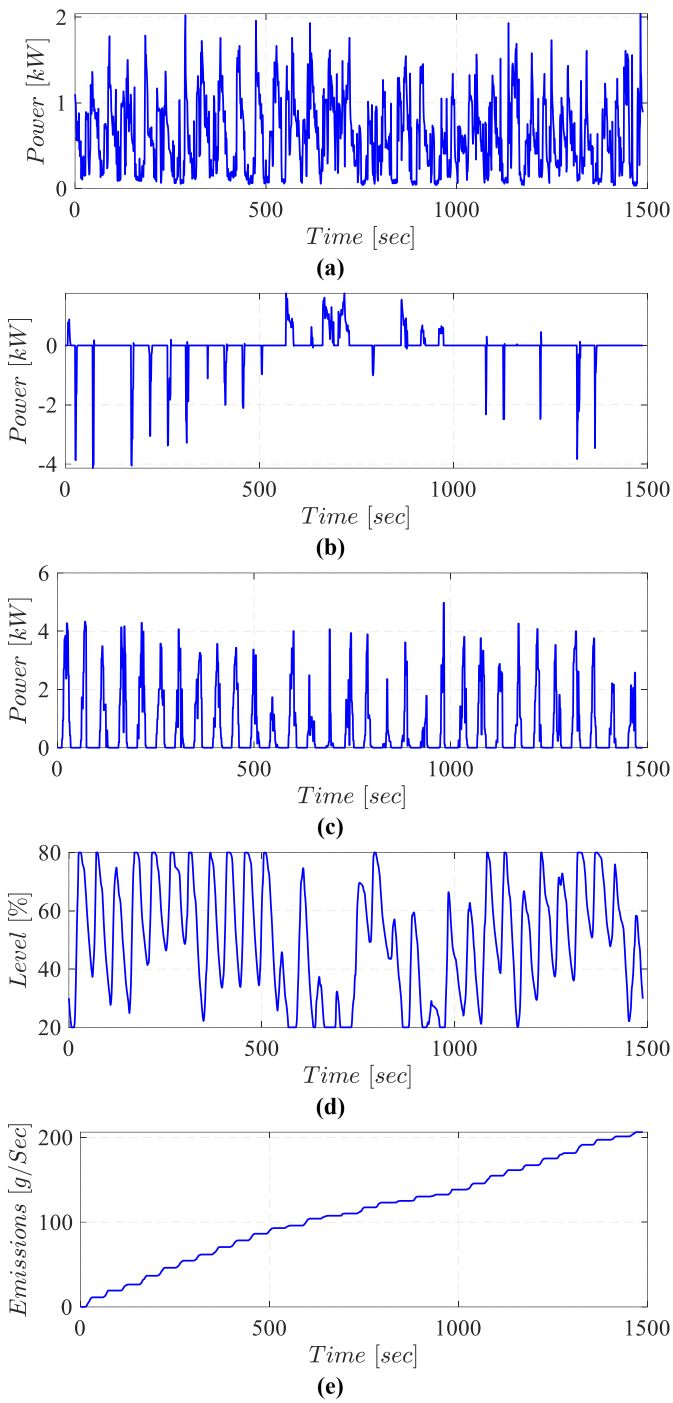
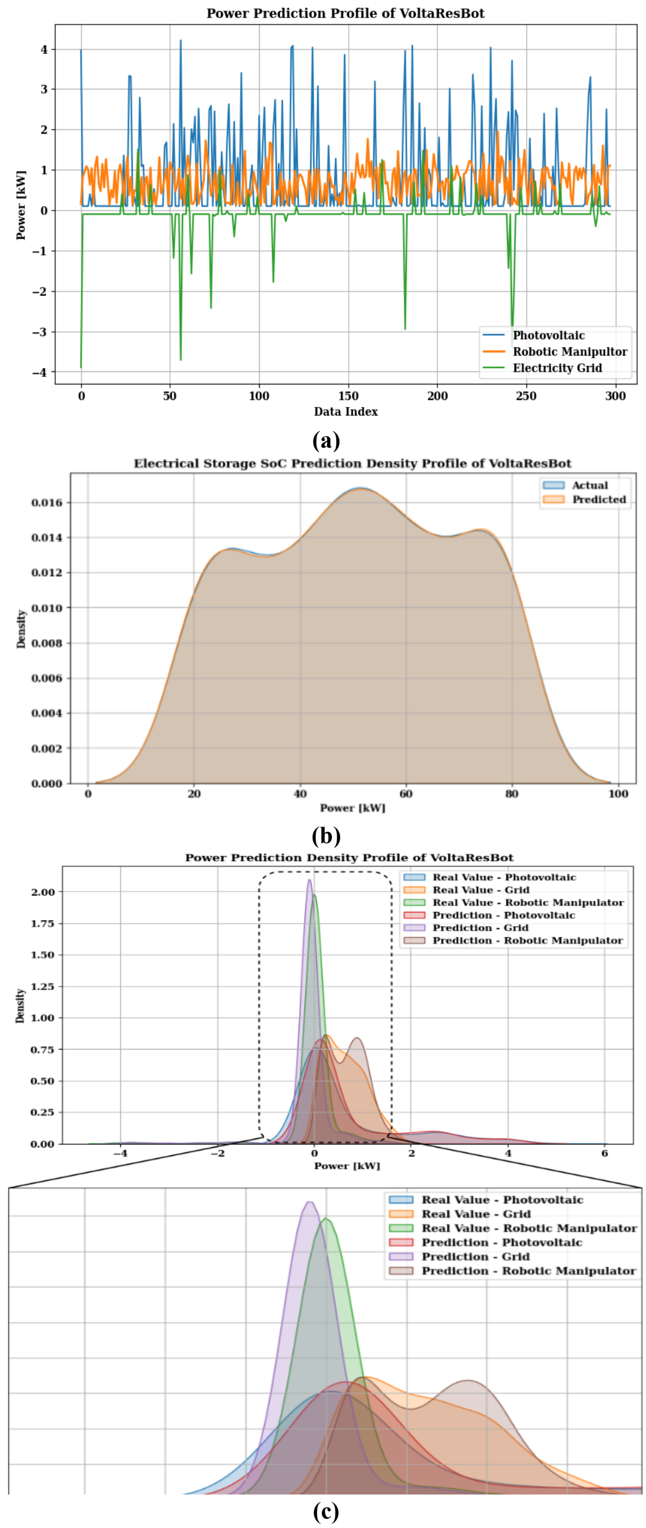
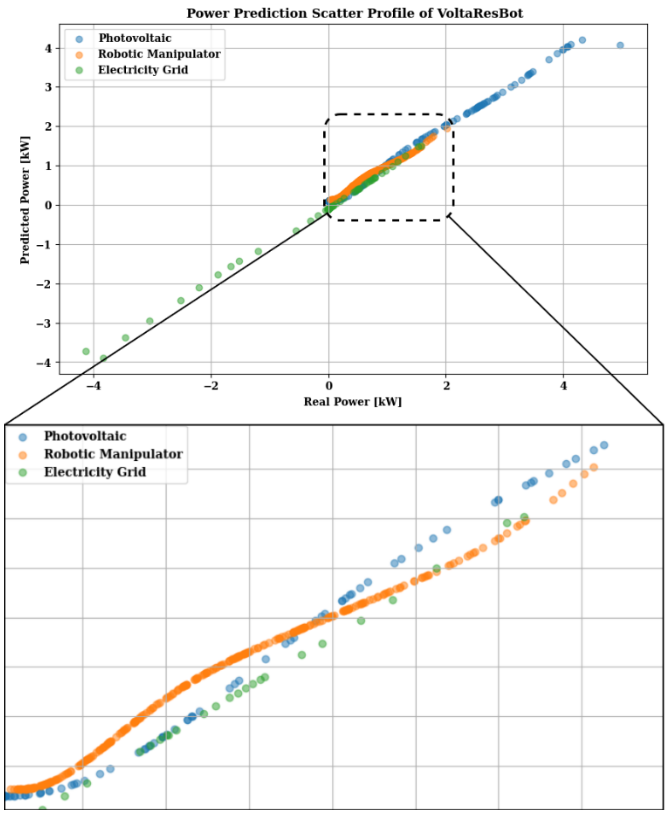


Fig. 4. The system identification plots of (a) Robotic manipulator electrical power consumption, (b) Electrical power drawn from or fed to grid, (c) Solar panel power profile near robotic manipulators, (d) Electrical energy storage state of charge level, and (e) Greenhouse CO2 gas emissions from the system





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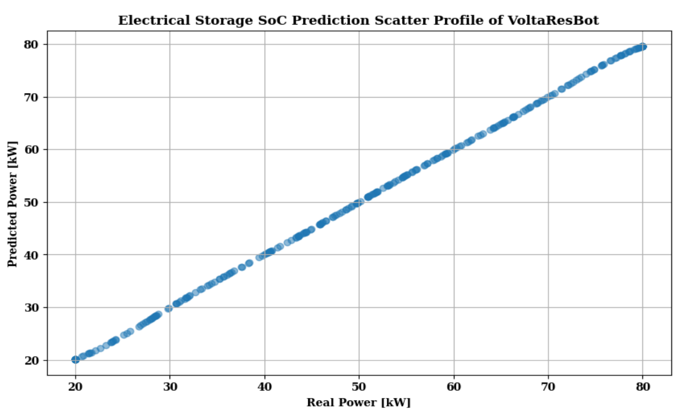


(e)

Fig. 5. The results derived by VoltaResMan in (a) Consumption profile, (b) Desntiy profile of SoC, (c-d) Consumption density/scatter profile, and (e) scatter results

As depicted in Fig. 5, VoltaResBot has improved system control and efficiency by integrating PV systems and reducing grid dependence and greenhouse gas emissions. This harmonious synergy between panels and the manipulator's energy demands enhances operational efficiency, minimizes grid reliance, and reduces environmental impact. VoltaResBot's effectiveness in optimizing energy utilization and promoting sustainability is evident.

During the initial period (0-50), an impressive 2.5 kW of energy is seamlessly harnessed, showcasing the system's adeptness in maximizing energy utilization. In the subsequent time frame (50-100), the system maintains a steady output of approximately 3 kW, demonstrating sustained efficiency. Notably, in the 100-150 timeframe, the system optimally utilizes 0.5 kW, indicative of its adaptive and responsive energy management. As the timeline progresses into the 150-200 period, the system injects a substantial 2 kW into the main grid, presenting a financially advantageous scenario. This trend continues with about 3 kW injected during the 200-250 timeframe and approximately 4.5 kW during the 250-300 period.

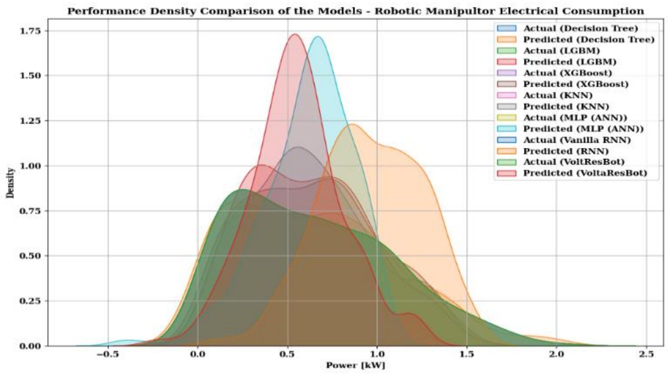
TABLE. I. VOLTARESBOT PERFORMANCE METRICS

Metric	Robot Cons. [kW]	SoC [%]	Grid [kW]	PV [kW]
MAE	0.054	0.1388	0.1002	0.0873
RMSE	0.0624	0.1774	0.1022	0.1023
MSE	0.0039	0.0315	0.0104	0.0105
R2	0.9794	0.9999	0.9659	0.9918

In this regard, VoltaResBot demonstrates performance in optimizing energy consumption across the integrated system, as reflected in its low MAE values: 0.054 for Robotic Consumption [kW], 0.1388 for SoC [%], 0.1002 for grid [kW], and 0.0873 for Photovoltaic [kW]. The RMSE values range from 0.0624 to 0.1774, with minimal MSE ranging from 0.0039 to 0.0105. Furthermore, the high R^2 values, reaching up to 0.9999, provide VoltaResBot's precision in predicting and optimizing energy dynamics, as the results are detailed in Table. 2, Fig.6.

TABLE. II. COMPARISON OF VOLTARESBOT WITH OTHER MODELS

Robotic Consumption [kW]				
Model	**MAE**	**MSE**	**RMSE**	**R^2**
Decision Tree	0.22599	0.123084	0.350834	0.348499
LGBM	0.215723	0.088	0.296647	0.534207
XGBoost	0.206188	0.087091	0.295112	0.539017
KNN	0.206922	0.086859	0.294719	0.540243
MLP	0.373649	0.212177	0.460627	-0.12308
RNN	0.49128	0.353497	0.594556	-0.8711
BiLSTM	0.294643	0.145277	0.381152	0.231033
VoltaResBot	0.054	0.0039	0.0624	0.9794
Grid [kW]				
Model	**MAE**	**MSE**	**RMSE**	**R^2**
Decision Tree	0.181925	0.399021	0.631681	-0.30316
LGBM	0.154794	0.232624	0.482311	0.240277
XGBoost	0.174348	0.369904	0.608198	-0.20807
KNN	0.146752	0.205757	0.453604	0.328022
MLP	0.26232	0.21855	0.467494	0.286239
RNN	1.392027	2.803329	1.674314	-8.15536
BiLSTM	0.234098	0.217013	0.465846	0.29126
VoltaResBot	0.1002	0.0104	0.1022	0.9659
PV [kW]				
Model	**MAE**	**MSE**	**RMSE**	**R^2**
Decision Tree	0.564638	1.247862	1.117077	0.016952
LGBM	0.511082	0.660623	0.812787	0.47957
XGBoost	0.446701	0.542158	0.736314	0.572896
KNN	0.335284	0.469937	0.685519	0.629791
MLP	0.743842	1.056157	1.027695	0.167975
RNN	2.110104	5.756908	2.399356	-3.53521
BiLSTM	0.592602	1.016001	1.007969	0.199609
VoltaResBot	0.0873	0.0105	0.1023	0.9918
SoC [%]				
Model	**MAE**	**MSE**	**RMSE**	**R^2**
Decision Tree	3.456881	47.90146	6.921088	0.870467
LGBM	5.425975	70.51299	8.397202	0.809322
XGBoost	4.191425	38.112	6.173492	0.896939
KNN	1.495331	5.97638	2.444664	0.983839
MLP	15.54065	370.28	19.24266	-0.0013
RNN	14.65408	290.2351	17.03629	0.215159
BiLSTM	12.58718	239.0162	15.46015	0.9918
VoltaResBot	0.1388	0.0315	0.1774	0.9999



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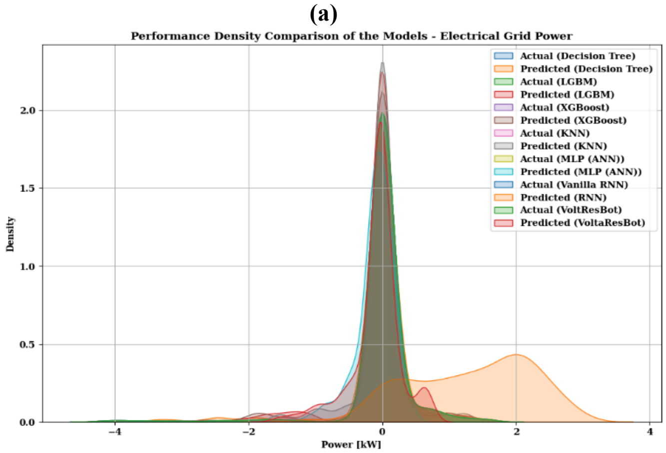

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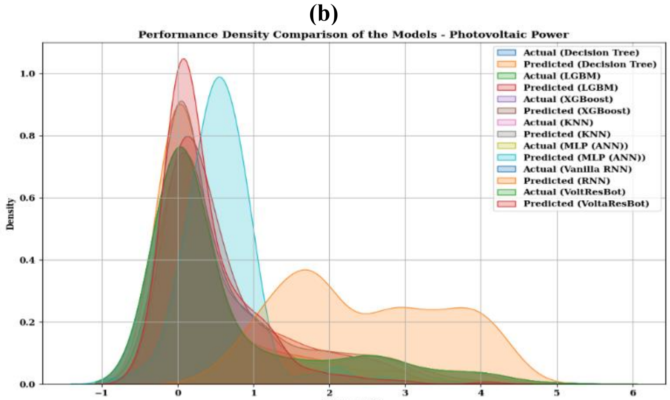

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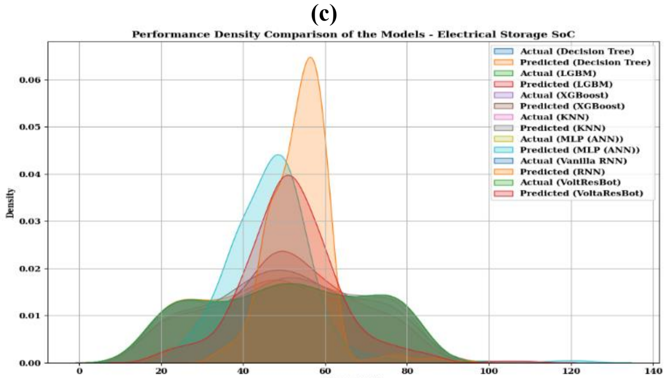

(d)

Fig. 6. The comparison performance of the models in (a) Robotic manipulator consumption, (b) Grid power, (c) Photovoltaic panels output, and (d) The storage level

From Fig. 6, VoltaResBot outperforms traditional machine learning models in forecasting robotic manipulator energy consumption, grid energy consumption, and photovoltaic energy prediction. Its accuracy is lower than that of traditional models such as XGBoost and KNN, while MLP, RNN, and BiLSTM show suboptimal performance. In predicting the SoC, VoltaResBot has the lowest MAE, MSE, and RMSE.

IV. Conclusion

This paper presented the importance of accurate predictive models in achieving sustainability, cost-effectiveness, and environmental efficiency. Motivated by the dynamic challenges inherent in modern robotic systems, VoltaResBot addressed existing gaps in precision and accuracy using advanced machine learning techniques, particularly SVM. Through comparative analyses against traditional models and KPIs of MAE, RMSE, MSE, as well as R^2, VoltaResBot demonstrated superior performance, emphasizing its capacity to adapt to the intricacies of multi-component systems. The model's success in accurately predicting and optimizing energy utilization positions it as an asset for industries aiming to enhance their operations' financial and environmental dimensions.

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