Energy Management of Renewable Energy Sources Based on Support Vector Machine

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Abstract- In recent years, Renewable energy has covered a growing portion of the global electrical power demand. Microgrids are gaining popularity as a promising technology in order to include renewable energy sources in the distribution system. These resource integrations, which include solar arrays, wind turbines, diesel generators, and battery storage systems, combined with load demand. The efficient integration of these DGs in a microgrid faces several obstacles, including the accuracy of energy predictions for renewable energy sources such as wind and solar, energy management, and economic dispatch (ED). depending on the data of renewable energy output and load forecasting in microgrid achieving the optimization of microgrid dispatch. In this paper, a system that relies on the machine learning algorithm is implemented to forecast. support vector regression (SVR) is a regression model that has been used for optimization. SVR is a type of support vector machine that can learn regression functions and is an extension of the support vector machine classification method. Enhance the precision of energy forecasts so that the electrical grid can run more efficiently. MIQP (mixed-integer quadratic programming) is used to define the whole problem, which can be solved quickly via Gurobi Optimizer.

Keywords Energy management, Microgrid, Machine learning, Support vector machine, Quadratic programming.

1. Introduction

In order to respond to climate change, the need for power is fast growing due to globalization and industrialization [1]. Renewable energy sources, such as wind and solar, are becoming more significant all around the world [2]. They are frequently referred to as negative loads due to the intermittent nature of weather [3]. Over the previous several years, a major integration of Distributed Energy Resources (DERs), involving renewable energy sources and storage units, has been recorded. Because renewable energy is inherently unpredictable, researchers have discovered that a high penetration of it could weaken the grid and possibly cause blackouts. Microgrids have been promoted as being one of the possible solutions to this challenge. [4]. The microgrid is a single controlled item that combines numerous distributed power, load, energy storage devices, and control devices to provide both electrical and thermal energy to the consumer. Microgrid technology has emerged as an effective proper solution for maximizing the use of distributed energy [5], [6]. The efficient integration of these DGs in a microgrid faces several obstacles, including the accuracy of energy forecasting for green power sources like solar and wind, energy management, and economic dispatch (ED).

In both grid-tied and islanded modes of operation, an Energy Management System (EMS) is necessary to regulate power flow and balance supply to load in a microgrid [7]. The two most common reasons for a microgrid to go into autonomous mode are transmission maintenance and transmission feeder failures [8]. The economic dispatch (ED) problem is concerned with determining the power outputs of online producing units in order to meet system load at the lowest feasible cost while meeting system restrictions. [9]. Static dispatch and dynamic dispatch are two types of economic power system dispatch. [2]. In static economic dispatch, the best price of a test model is determined for a single demand [9]. Because it not only searches for minimum operating cost in a scheduling loop but also includes multiple various distributed generators (DG) throughout numerous periods, the Dynamic Economic Dispatch issue (DED) must fulfill the system's operational demands in real time [11], [1].

A large number of algorithms, including mixed-integer linear programming and meta-heuristic methods like particle swarm optimization and genetic algorithm, sequential quadratic programming, and interior-point algorithm, have been proposed recently because of the multi-faceted complexity of the microgrid UC & ED issue [12], [13]. Mixed integer quadratic programming (MIQP) is proposed for solving the UC and ED problems for its high efficiency and modelling flexibility, and the availability of promising commercial solutions [12], [14], [15].

Based on the data of renewable energy output and load forecasting in microgrid achieving the optimization of microgrid dispatch. As a result, energy prediction is vital in the electricity sector. Accurate power load forecasting is essential to decreasing energy consumption, reducing the price of power generation, and increasing social and economic merits. [16]. So that solar and wind energy resources can be utilized to their full potential Accurate resource forecasting is critical [17]. Machine learning (ML), a type of artificial intelligence, has gained a lot of traction in recent years [4]. Solar and wind energy resources have been predicted using a variety of methodologies. The effectiveness of the support vector machine modelling technique was shown to be preferable to other modelling approaches in terms of forecasting. The support vector machine is quick, easy to operate, and produces precise results. Support vector machine models, according to studies based on critical analysis, can produce significantly higher precision than other models [17].

The contributions of this paper are:

- A formulation of the energy management issue with renewable microgrids, storage devices, and a diesel generator is described.
- Employing support vector regression algorithm for solar power, wind power and, load demand forecasting.
- The grid search of the SVR's hyper-parameters is conducted to find out the optimal penalization parameter (C) and Gamma by using a cross-validation technique
- Implementation of the proposed method to obtain the optimal solution to the problem of ED problem with quadratic objective cost functions and constraints

The paper is arranged as follows: Microgrid modelling is described in Section 2. Section 3 introduces the problem. Section 4 presents the suggested optimization technique. the outputs of simulation are shown in Section 5. Finally, Section 6 provides the work to a conclusion.

2. Microgrid Modelling

In this paper, the Microgrid consists of the PV array model, wind turbine, energy storage batteries, a diesel generator, and fixed and variable loads as shown in Fig 1.

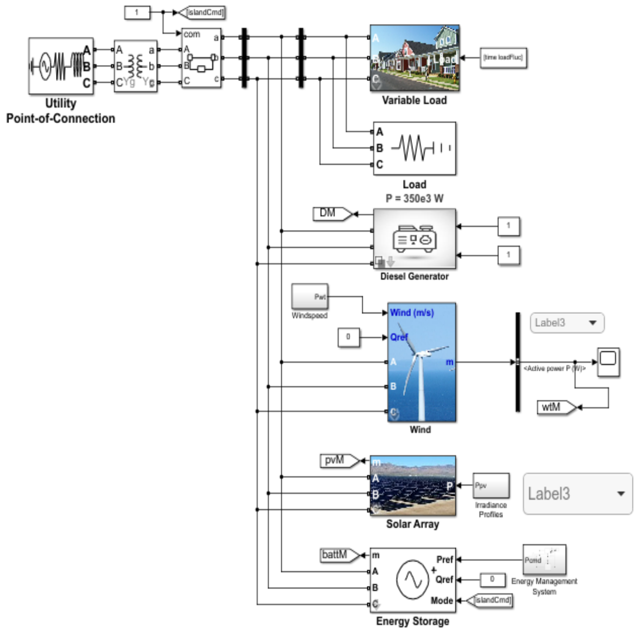

Fig. 1. Layout of Microgrid

2.1. Photovoltaic Model

The photovoltaic effect is a semiconductor-based mechanism for turning the sun's radiation into a direct current. [18], [19]. The number of cells in a PV module, the type of cells, and the total surface area of the cells all impact the module's power output. The quantity of energy generated by solar panels can be determined using the size of solar panels distributed in our system and the global irradiance provided to every hour of the day published in [20]. This paper uses the sub-hourly (5-minute) weather data. Using the following equation:

$$P = I_{rr} * A_{pv} * K_t \tag{1}$$

Where:

- P [W]: Power output , I_{rr} [W/m2]: Irradiance , A_{pv} [m2]: Solar panels surface

- K_t [%]: Global efficiency of the PV solar installation

2.2. Wind Turbine

The kinetic energy (wind energy) in the air is converted into electricity by a wind turbine. According to meteoro - logical data conditions [20], Cairo is not an especially windy area. As a result, a low start-up wind speed becomes one of the most important factors to consider when choosing a wind turbine. Due to these considerations, the following wind turbine was selected in the literature [21].

The power of the wind can be defined as [22]:

$$P = \frac{1}{2} * \rho * A * V^3 * C_p \tag{2}$$

Where: - A [m2]: swept area at speed V [m/s], ρ [kg/m3]: air density. - Cp: coefficient of power of rotor, the fraction of the wind's power that is obtained by the blades.

2.3. Battery

The Microgrid's batteries serve a dual purpose. One of its functions is to serve as a backup or UPS system, supplying the loads in the event of a power outage. The second function is to reduce the Microgrid's operating costs by charging the batteries with surplus PV or wind power and releasing them to decrease the amount of energy required by the auxiliary generators. The system's battery capacity is 2500 KWh.

2.4. Auxiliary Generators

Because RERs have alternate output characteristics, they typically limit user-side demand when connected to the utility grid. In general, DG is a critical component in the design of a microgrid network because it has several advantages in terms of emergency reserve power, system dependability, time-consuming power, prime power, and ongoing providing power [23]. Generators of various sizes are available from the chosen generator supplier. The 60 kw diesel generator was chosen.

2.5. Load

The load demand for MG consists of fixed and variable loads, resulting in a total load. The load consists of 12 days. loads of the third day are the same as loads of the fourth, ninth and tenth days, and loads of the fifth day are the same as loads of the sixth and twelfth day, and loads of the seventh day are the same as loads of the eighth day as shown in fig 2.

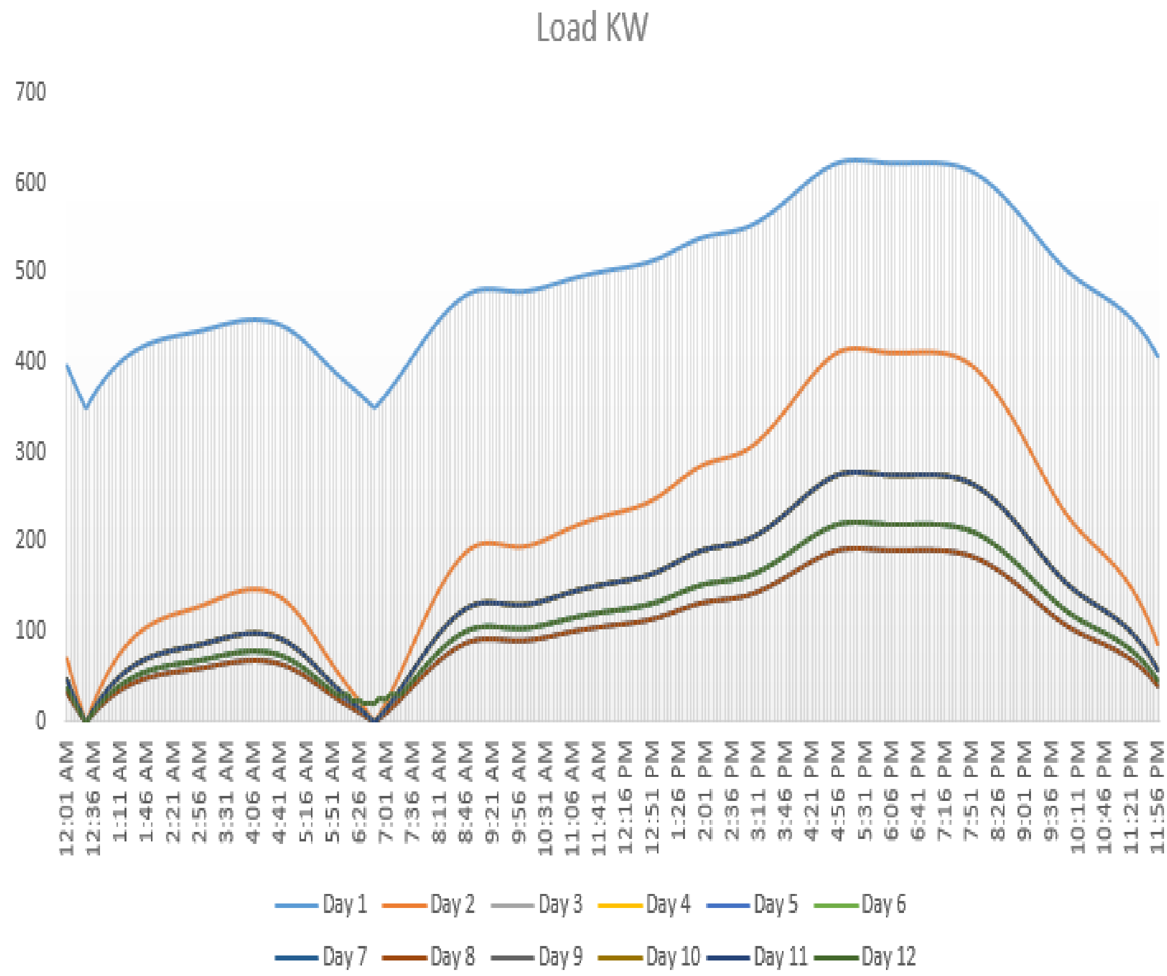

Fig. 2. Values of total load demand

3. Problem Formulation

The forecasting of these renewable resources has become a vital tool in the operation of power systems and markets. This paper uses support vector regression. (SVR) is a machine learning technique that relies on the statistical learning principles [16]. The primary concept behind this approach is to identify a hyper-plane by using nonlinear mapping to turn a nonlinear input region into a high-dimensional area. SVMs are commonly used for classification, pattern recognition, and regression. they outperform other procedures,such as conventional statistical models that were investigated previously. Support vector regression is the SVM used to approximate functions and regression.Several essential functions of the kernel are utilized in SVM models. Different types of functions including polynomial (Poly), exponential radial basis function (ERBF), radial basis function (RBF), sigmoid, and linear are investigated in the literature [17], [24]. Optimization and the kernel used in SVR forecasting are presented. The regression model can be developed, as demonstrated in Equation (3):

$$\gamma = \omega^{T}\theta(\chi) + b \quad (3)$$

where ω is the weight vector, b is the bias term and θ(χ) is a nonlinear mapping function that translates χ onto a higher-dimensional feature space. To get ω, it is essential to reduce the following regularized expression, which can be described in Equation (4), with the constraint of Equations (5-7).

$$\min\left\{\frac{1}{2}\omega^2 + C\ \sum_{i=1}^{N}\left(\{\xi_i + \xi_i^{(*)}\}\right)\right\} \quad (4)$$

$$\gamma_i - \{(\omega^{T}\theta(\chi) + b)\} \leq \psi + \xi_i \quad i = 1.2. \dots .N \quad (5)$$

$$\xi_i . \xi_i^{(*)} \geq 0 \quad i = 1.2. \dots .N \quad (6)$$

where ψ is equal to the function approximation precision positioned on the training data samples. ξ_i.and $\xi_i^{(*)}$ symbolize the positive slack variables and C is the error's penalization parameter, which is used to manage the trade-off between regularisation and empirical risk. Ultimately, the SVR is solved by using Lagrange multipliers δ_i. and $\delta_i^{(*)}$ and utilizing the constraints, which have the following form:

$$f(\chi) = \sum_{i=1}^{N}\left(\delta_i - \delta_i^{(*)}\right)K(\chi.\chi_i) + b \quad (7)$$

Kernel functions are also used to get the best results on non-linear separable data. A kernel function may be thought of as a pattern similarity measure, and it's very beneficial for non-linear regression problems.
In our studies, we use an RBF-kernel:

$$K(\chi.\chi') = \exp\left(-\frac{\|\chi-\chi'\|}{2\sigma^2}\right) = \exp(-\gamma\|\chi - \chi'\|^2) \quad (8)$$

Here, γ > 0
A flowchart for the SVR method is shown in fig.3 [25].

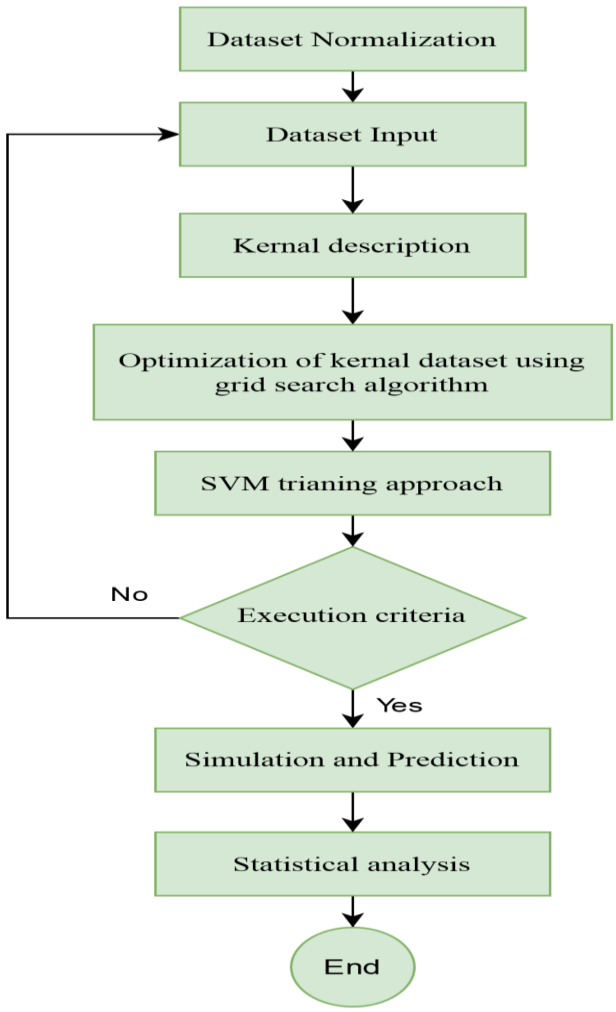

Fig. 3. Flow chart of SVM model with search algorithm.

Based on the data of renewable energy output and load forecasting in microgrid achieving the optimization of microgrid dispatch. The core aim of the ED issue is to arrange the generation of committed power sources in a method to minimize operational costs while following all system restrictions.

3.1. Objective Functions

3.1.1 Minimization of the Economic Dispatch Cost

The objective function of ED problem is as follows [26], [1], [9],[27]:

$$\text{Minimize } F_T = \sum_{i=1}^{n} F_i(P_i) \quad (9)$$

Where
P_i is the active output power of the i^{th} DER, $F_i(P_i)$ is the generation cost of the i^{th} DER, and the Cost functions can be expressed as:

$$F_T = F_{Diesel} + F_{Battery\ discharge} \quad (10)$$

The most common cost function of each generator can be constructed as a quadratic cost function as follows:

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 \tag{11}$$

Where
ai, bi, and ci are three cost coefficients of the i^{th} DER, and they can be expressed as:

$$F_i(P_i) = 2.6975 + 1.11153P_{Diesel} + 0.05P_{Diesel}^2 + 0.1154 + 0.7975P_{Battery\ discharge} + 0.1409P_{Battery\ discharge}^2 \tag{12}$$

3.2 Constraints

In generating capacity restriction, the power output of each producing unit should be between its minimum and maximum limits.

$$P_i^{min} \le P_i \le P_i^{max} \tag{13}$$

Where Pi^{min} and Pi^{max} are the minimum and maximum boundaries of the i^{th} DER, respectively, which has the following form:

$$0 \le P_{Diesel} \le P_{Diesel}^{max}$$

$$0 \le P_{batterydischarge} \le P_{battery\ discharge}^{max} \tag{14}$$

$$P_{Diesel+}P_{batterydischarge} = \text{net load}$$

3.2.1 System power balance

ED issue is subjected to the power balance and generating capacity constraints. In power balance constraints, the total energy production must fulfill overall system consumption. In this paper, the transmission system loss is ignored for all test systems. It can be expressed as follows:

$$\sum_{i=1}^{n} P_i = P_D \tag{15}$$

Where P_D is the total system demand

And net load for power dispatch can be expressed as:

$$\text{net load} = P_{load} - P_{Solar} - P_{wind} \tag{16}$$

where $P_{load}.P_{Solar}$ *and* P_{wind} are power predict of Solar ,wind and load

4. PROPSED OPTIMIZATION ALGORITHM

In a mixed integer programming (MIP) problem, both integer and continuous variables can be used. A Mixed Integer Quadratic Program is a problem in which the objective function has a quadratic term. When the cost function is quadratic and the restrictions are linear, (MIQP) successfully optimizes the objective function to obtain the optimal dispatch. This paper uses the Gurobi MIP platform to tackle problems with a quadratic objective [28], [29].

$$\text{Minimize } \frac{1}{2}\, x^T Q\, x + q^T x$$

$$\text{Subject to } A_{eq}\ x = b_{eq} \text{ (linear constraints)}$$

$$l \le x \le u \text{ (bound constraints)}$$

Some or all of x must be integers (integrality constraints)

where

X: vector of n variables
Q: n × n-dimensional real symmetric matrix
q: a real-valued, n-dimensional vector c
A_{eq}: real matrix ,Linear equality constraints.
b_{eq}: real vector ,Linear equality constraints
l , u: upper and lower bounds of the of the i^{th} DER, respectively.

A flowchart of the planned strategy is shown in Fig 4

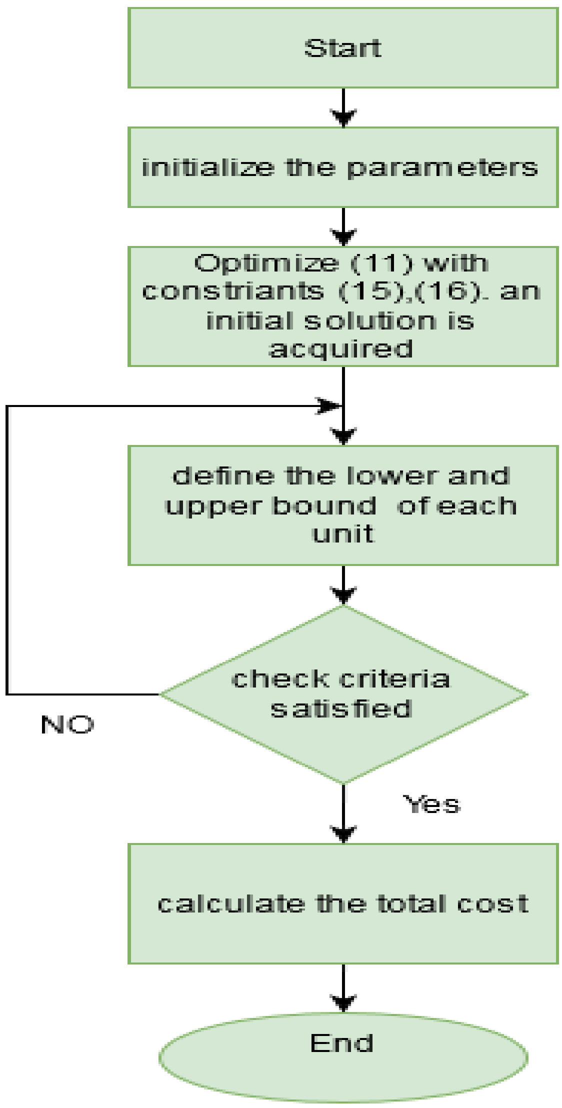

Fig. 4. Flowchart of the suggested method to solve ED.

5. Results and Dicussion

The configuration of the tested MG is shown in Figure 1. The optimized EMS is used to solve the problem of energy usage for an MG during a 24-hour period. in this case, The MG has been isolated from the utility and is operating in an autonomous mode. The load profile of this scenario is shown in Figure 2. Throughout this research, the proposed algorithm will have to decide the optimal way to dispatch of battery and diesel generator. The proposed method has a number of important parameters that should be selected before its execution in order to get the optimum solution.

All the simulation studies were performed on 2.8-GHz i3 PC with 8 GB of RAM using ANACONDA and Gurobi Optimizer. The data set is split into two sections: the test and training. Training data includes Day 1 and Day 2, while the test set involves data from day 4 to day 12. The data description of MG is illustrated in table 1.

Table 1. statistical data description of MG

	Temp (°C)	Load (kw)	Radiation (W/m^2)	Solar Power (kw)	Wind speed (m/s)	Wind power (kw)
Count	3450	3450	3450	3450	3450	3450
Mean	22.097	166.088	236.816	177.612	3.596	15.771
STD	7.901	129.231	319.255	239.441	1.782	34.675
min	6.500	0.260	0.000	0.000	0.300	0.004
25%	15.900	77.446	0.000	0.000	2.400	2.392
50%	22.400	132.670	8.000	6.000	3.100	5.156
75%	28.1000	214.383	484.000	363.000	4.200	12.824
Max	37.700	626.801	1011.000	758.250	12.000	299.103

There are a variety of approaches to explore feature significance. A correlation graphs are a simple way to study correlation as shown in fig 5.

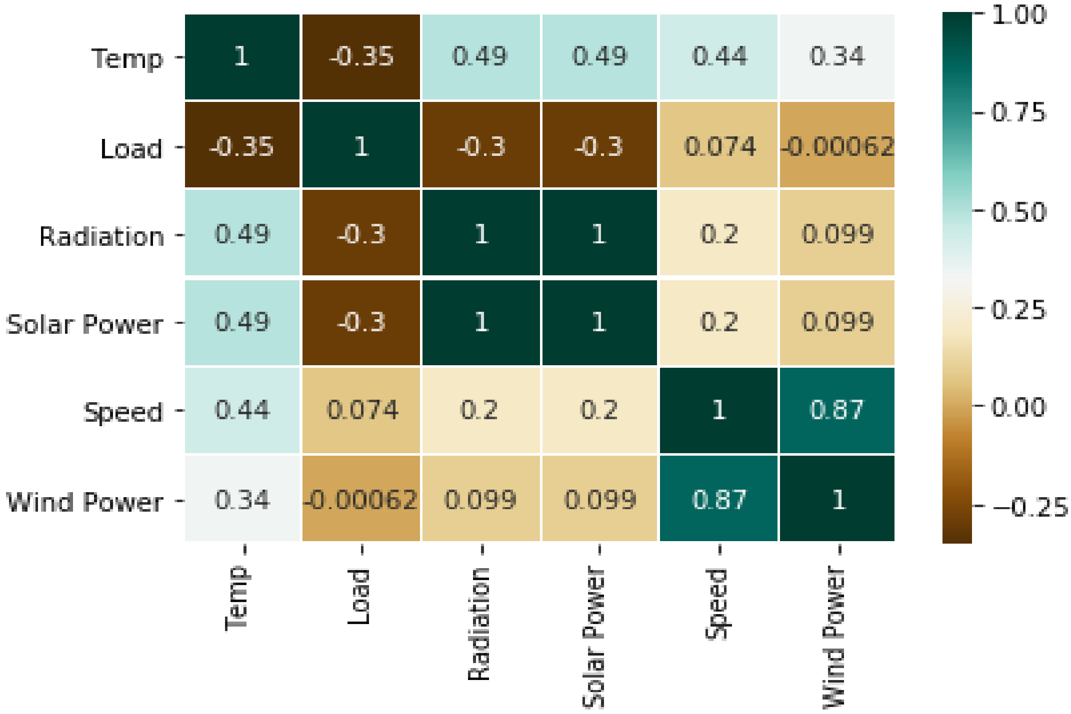

Fig. 5. correlation graph for Data of MG

In this paper, the SVR is optimized for PV, wind power, and load forecasting. The grid search of the SVR's hyper-parameters is conducted to find out the optimal C (regularization parameter) and Gamma. In other words, searching for SVR's parameters give a minimum Root mean squared error (RMSE) and a higher R-squared score. A cross-validation strategy is used to create the search grid. The optimum parameter of C and gamma are 50, 0.01 respectively as shown in table 2.

Table 2. The optimum parameter of C and gamma of SVR

Kernel	C	Gamma	Load Forecasting		Wind Power Forecasting		Solar Power Forecasting	
			RMSE	R^2	RMSE	R^2	RMSE	R^2
RBF	0.001	0.01	27.99	-4.7	10.61	-0.09	41.06	-0.45
	0.001	0.001	28.48	-4.9	10.70	-0.11	42.43	-0.556
	0.001	0.0001	28.5	-5.02	10.71	-0.117	42.57	-0.56
	0.001	1e-5	28.54	-5.02	10.71	-0.118	42.59	-0.56
	0.1	0.01	3.70	0.89	8.26	0.33	4.60	0.981
	0.1	0.001	22.80	-2.8	9.72	0.079	26.88	0.37
	0.1	0.0001	27.97	-4.7	10.60	-0.096	40.96	-0.45
	0.1	1e-5	28.48	-4.9	10.70	-0.11	42.43	-0.556
	10	0.01	0.50	0.9981	2.88	0.91	0.76	0.999
	10	0.001	1.28	0.98	5.12	0.744	0.94	0.999
	10	0.0001	3.43	0.91	8.21	0.342	4.33	0.983
	10	1e-5	22.78	-2.8	9.71	0.08	26.78	0.379
	25	0.01	0.35	0.999	2.56	0.936	0.63	0.999
	25	0.001	0.64	0.996	3.59	0.874	0.77	0.999
	25	0.0001	2.37	0.95	7.50	0.45	3.00	0.992
	25	1e-5	14.43	-0.53	9.00	0.209	11.63	0.88
	50	0.01	0.31	0.999	2.48	0.939	0.61	0.999
	50	0.001	0.50	0.998	3.10	0.906	0.69	0.999
	50	0.0001	1.81	0.975	6.60	0.57	1.62	0.997
	50	1e-5	5.72	0.75	8.59	0.280	5.76	0.971
	100	0.01	0.32	0.999	2.44	0.941	0.62	0.999
	100	0.001	0.42	0.998	2.81	0.922	0.65	0.999
	100	0.0001	1.24	0.988	5.14	0.742	0.87	0.999
	100	1e-5	3.43	0.913	8.21	0.342	4.33	0.983
	1000	0.01	0.31	0.999	2.35	0.94	0.70	0.999
	1000	0.001	0.32	0.999	2.35	0.946	0.65	0.999
	1000	0.0001	0.43	0.998	2.78	0.924	0.64	0.999
	1000	1e-5	1.23	0.988	5.17	0.739	0.89	.999

5.1 Forecasting Results

The comparison of actual and forecasted solar power, wind power, and load demand values is depicted in Fig 6-8 As we stated , the suggested model is trained on day 1,2 and test data on day 5. the weather data input is sub-hourly (5-minute).

5.1.1 Forecasting of Solar Power

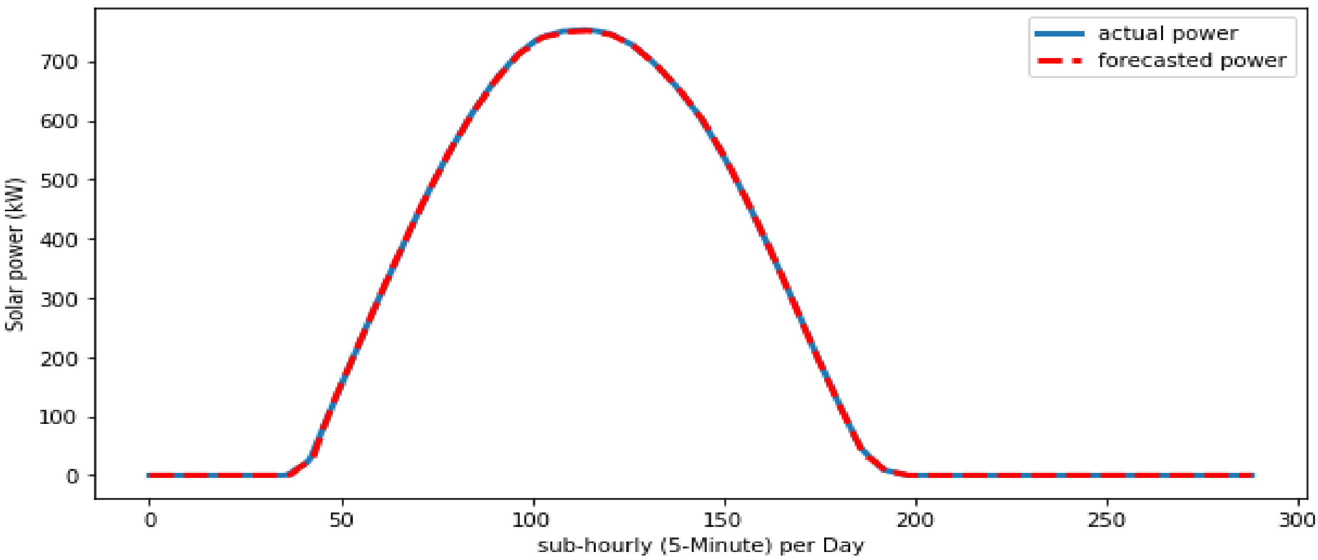

Fig. 6. Actual and forecasted of solar power values.

5.1.2 Forecasting of Wind Power

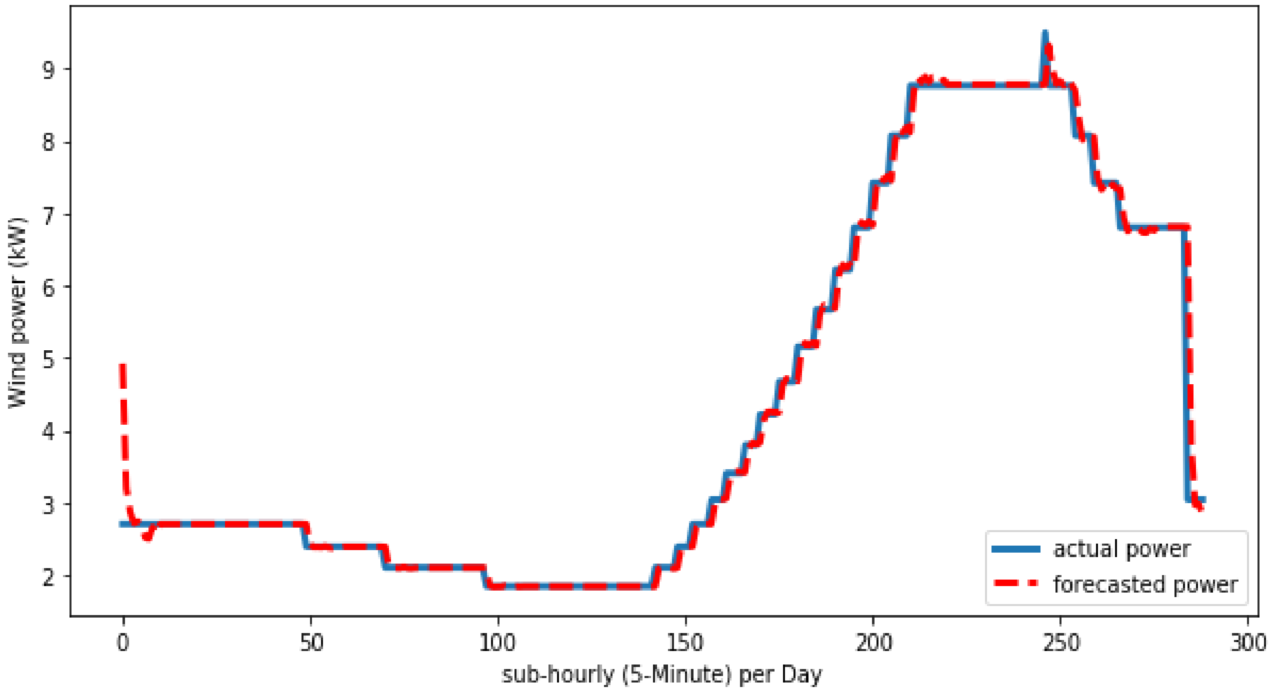

Fig .7. Actual and forecasted of wind power values.

5.1.3 Forecasting of Load Demand

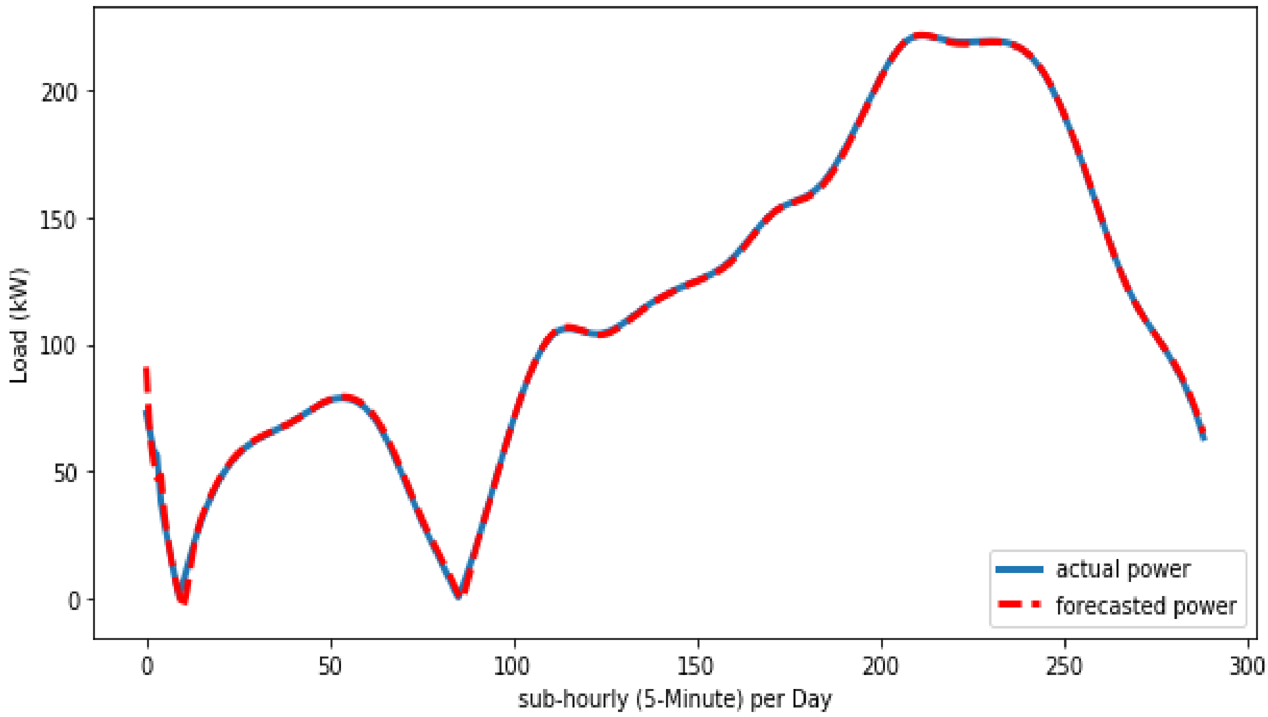

Fig .8. Actual and forecasted of load demand values.

5.2 Economic Dispatch Analysis

The solution to the problem of finding the lowest cost in microgrid energy dispatch was presented in Figure 1 which corresponds to the case study and was based on the Economic dispatch algorithm with the gurobi solver through quadratic regression, which produced the results displayed in Fig 9,10.

5.2.1 Economic dispatch for battery

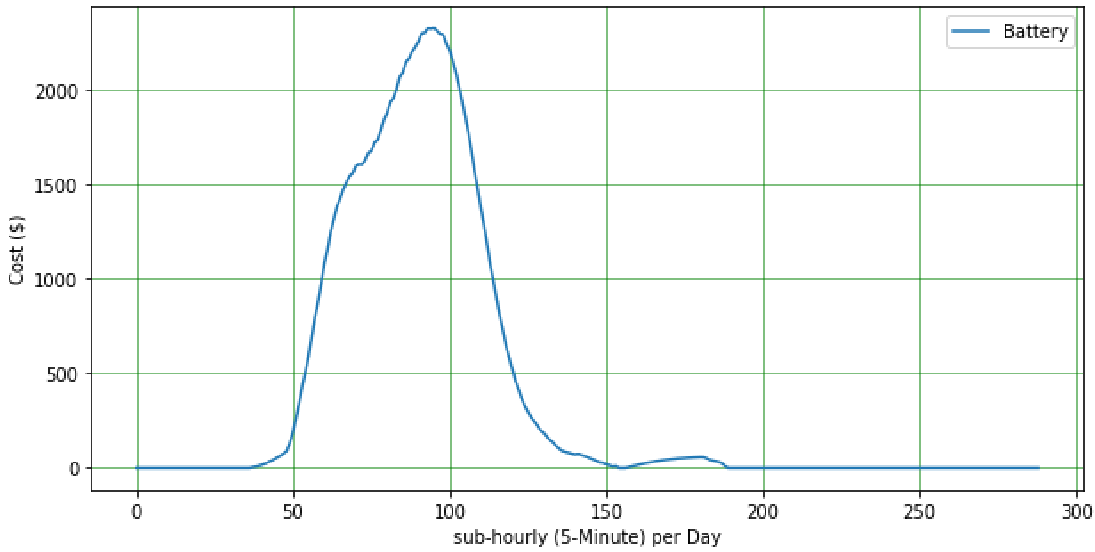

Fig .9. cost analysis of economic dispatch for battery

5.2.2 Economic Dispatch for Diesel Generator

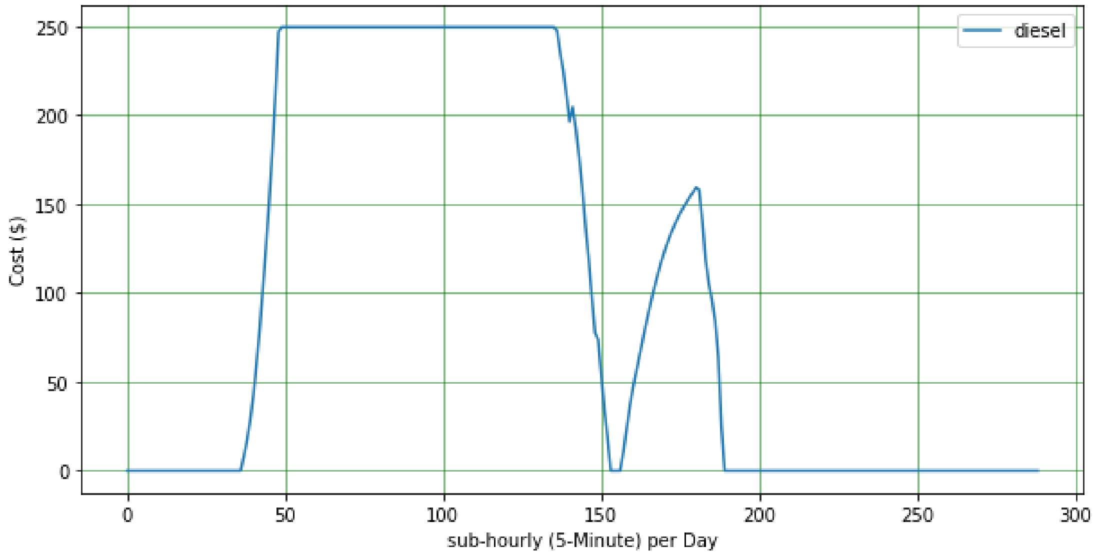

Fig. 10. Cost analysis of economic dispatch for diesel generator

Conclusion:

Microgrids are generally composed of PV solar, wind turbine, diesel generator, battery energy storage, load demand, and microgrid energy management system. Efficient integration of these DGs in a microgrid, depends on the accuracy of energy forecasts of dependent renewable energy sources, i.e., wind and solar, energy management, and economic dispatch (ED). These exact projections will enable the most efficient use of sustainable and renewable energy sources, reducing the negative impacts of fossil fuel consumption. This paper investigated using support vector regression for solar power, wind power, and load demand forecasting. Because of its predictability and accuracy, this model has gained the attention of many researchers across the world and is now widely used. The best accuracy and minimum RMSE results by the SVR algorithm are achieved by using the parameter of C and gamma 50, 0.01. In this paper mixed integer quadratic program (MIQP) for solving ED problems with quadratic cost functions and constraints are linear has been researched. The obtained results by the suggested algorithm in 24 hr periods of analysis in the study. Simulation results of the proposed modelling under ANACONDA and Gurobi Optimizer are presented.

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