Name:B.vinothini
Reg.No:422221104048
College Code:4222
Team:T4

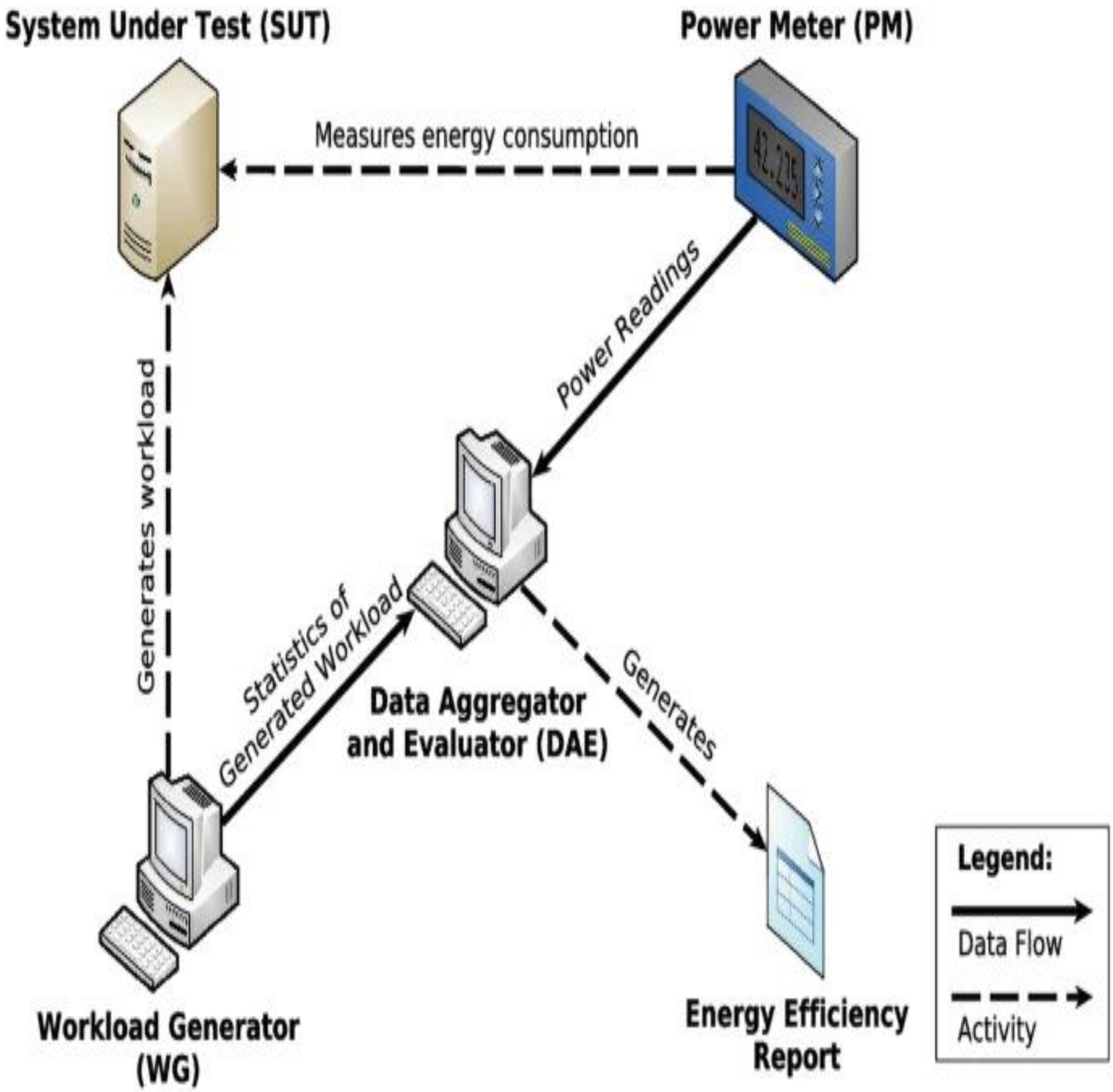
MEASURE ENERGY CONSUMPTION

Introduction

Energy consumption and emissions of harmful gases are of increasing concern in the world, and alternative options are continuously being explored having a reduced effect on the environment. Traditional electricity production process principally depends upon critically limited fossil fuels. The process of electricity generation by means of these fuels, several poisonous by-products adversely affect the conservation of natural eco-system.

Diesel engines are mainly used for decentralized power generation. The major drawback of these engines is the emanation of harmful gases. However, various studies claim that using other similar fuels or dual-fuel (using foreign fuel as partial substance) in these engines can significantly affect the emissions and can produce power from a few kilowatts up to several hundred kilowatts. R. Uma et al. (2004), stated that dual-fuel operation reduces NO_x and SO_2 emission without increasing particulate emission at the expense of an increase in carbon monoxide emission. Saleh (2008) studied the effect of variation in LPG composition on emissions and performance in a dual fuel (LPG-diesel) diesel engine. B.B. Sahoo et al. (2012) discussed the effect of H_2: CO ratio in syngas on the performance of a dual fuel diesel engine operation. H. Ambaria (2017) elucidated performance and emission characteristics of a small diesel engine run in dual-fuel (diesel-biogas) mode. An appropriate trade-off between the operating diesel engine on different fuel mode will result in balanced emissions and energy consumption.

To address this challenge, support vector machines (SVM), a machine learning tool is adopted to classify feasible data from the data set in order to define a design space to operate the engine with constrained objective limits to produce electricity. The model can be used to classify the data from the embedded dataset and considered to be more reliable as it encompasses a data-driven approach. The aim of this paper is to obtain a design space for constrained energy consumption and different emission limits. The study is based on emission and energy consumption characteristics of the electricity generation system using a diesel engine. The proposed methodology is explained using literature example. The diesel engine can be operated in two different modes i.e. diesel alone and dual fuel (diesel-producer gas). In order to operate similar engines parallelly in two different modes, a design space is created using an SVM classifier. This will assist the planner to make decisions in a defined area and to optimize several objectives within the calculated predefined area using classifier algebraic equation.



System Under Test (SUT)
Power Meter (PM)
Measures energy consumption
42.225
Power Readings
Generates workload
Statistics of Generated Workload
Data Aggregator and Evaluator (DAE)
Generates
Workload Generator (WG)
Energy Efficiency Report
Legend:
Data Flow
Activity

Specific energy consumption

Specific energy consumption (SEC) calculation method is one of the basic approaches to calculate unit energy consumption of a product. In the calculation of SEC the number of energy consuming unit (J) that are associated with energy consumption, the average amount of energy (E_t) that is used during period (t), and the quantity of production (P_t) that is produced during period (t) are involved.

$$\text{SEC} = J * E_t / P_t$$

Close tracking of the SEC value for production processes is substantial to follow the energy use per unit product in severe circumstances of global market competition and increasing environmental compulsions over the manufacturing industry.The textile industry as part of the global competitive manufacturing sector is one suitable ground for SEC calculation. Estimated SEC data of a textile product can easily be transformed to the energy footprint of a unit (kg, meter, or piece) textile product. SEC data can also be utilized both for operating profit margins per product and also for indication of machine safety.

Energy consumption of the static mixer

Energy consumption is one of the main concerns for the application of the static mixer to the hydrate formation process. In this section, estimation of the energy consumption was conducted based on the present experimental conditions. Assuming the temperature conditions and pressure conditions of the fluids were prepared for the hydrate formation, we focused on the energy consumption for the hydrate formation in the static mixer; the energy consumption for the pumping of the fluid in the mixer. The pumping energy for the fluid into a pipe, ε_v [W/kg-total flow] under a turbulent flow condition is given by Eq. (1),

(1) $$\varepsilon_v = \frac{Q\Delta P}{V\rho} = \frac{\Delta P}{\tau\rho}$$

where ΔP is the pressure drop along the pipe and Q [m^3/sec] is the flow rate, and V is the inner volume of the pipe, and τ[s] is the residence time of the fluid in the pipe. For the Kenics type static mixer, the pressure drop can be given by the following equation;

(2) $$\Delta P = 4 f_{SM} \frac{L}{D} \frac{\rho u^2}{2}$$

where f_{SM} [-] is the friction coefficient of the mixer, D is the inner diameter of the mixer, L is the mixer length, ρ [kg/m^3] is the density of the fluid, and u is the average fluid velocity [m/s]. The friction coefficient of the Kenics-type static mixer is given by the equations as an empirical function of Reynolds number, Re [19].

The energy consumption for the pumping into the static mixer was calculated assuming the following condition based on the present experimental results for the case of dispersed hydrate formation; water flow rate = 2,980 mL/min, CO_2 flow rate = 93.4 mL/min. It is assumed that the fluid properties of two-phase flow could be replaced by those of water. The pressure drop for this case is, ΔP = 14.1 kPa, and the energy consumption is, ε_v = 45.3 W/kg-total flow, equivalent to the energy consumption per unit mass of CO_2 flow = 1.66 kW/kg-CO_2 flow. Since the residence time of liquid CO_2 in the static mixer is 0.31 s in this case, the energy consumption per 1 kg of CO_2 is 0.52 kJ/kg-CO_2 assuming the conversion to hydrate in the mixer is 100 %. This result is about half of the case for the stirring vessel, of which the energy consumption for the hydrate formation (agitation energy) is about 1.1 kJ/kg-CO_2 [14] based on a laboratory-scale experiments.
From the above estimation, the application of the static mixer to the hydrate formation would have a large advantage in terms of energy consumption over

the stirring vessel reactor, and a continuous hydrate formation process could be constructed by using the Kenics-type static mixer as a hydrate formation device with lower energy consumption.

Conclusion

The energy consumption of a WWTP is a complex function and is influenced by several factors. In this paper, machine learning algorithms were used to create a suitable model that could predict the energy consumption of WWTPs. Historical data affecting energy consumption was taken into consideration for developing four different models. Developed models were compared based on MAE and RMSE for predicting energy consumption. GRU architecture gave the best results with the lowest error when tested on the entire dataset. The dataset's size and the data's complex characteristics became a significant hindrance in achieving greater accuracy. More parameters can be explored in future work, affecting energy consumption to predict outputs more accurately with a more extensive and well-correlated dataset. Also, significant developments in the model architecture, in terms of an ensemble model with a combination of ANNs, convolutional neural networks, and sequence models, will be explored as future research.