# USING ARTIFICIAL INTELLIGENCE TO CALCULATE SOLAR COLLECTOR PARAMETERS

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*KEYWORDS*

Artificial Intelligence, Machine Learning, Solar Energy, Solar Collector, Parameter Estimation, Energy Efficiency, Thermal Performance, Neural Networks, Predictive Modeling, Optimization, Data-driven Analysis, Heat Transfer, Computational Modeling, Smart Energy Systems, Renewable Energy Systems

*ABSTRACT*

This study explores the use of Artificial Intelligence to predict and optimize key parameters of solar collectors, such as thermal efficiency and heat transfer rate. Traditional analytical methods are often limited by nonlinear environmental factors, while AI techniques like Artificial Neural Networks and Genetic Algorithms offer more accurate and adaptive modeling. Results show that AI-based models provide high prediction accuracy and can effectively optimize collector performance under varying conditions, improving the overall efficiency of solar energy systems.

## Introduction

In recent years, the issue of sustainable energy consumption and carbon footprint reduction has become increasingly pressing globally. The use of renewable energy sources, particularly solar energy, is seen as key to achieving climate goals and ensuring energy security. One promising solution for households is the use of solar collectors for hot water supply and partial coverage of building heating loads. The increasing global demand for clean and sustainable energy sources has made solar energy one of the most promising alternatives to fossil fuels. Solar collectors, which convert solar radiation into useful thermal energy, play a vital role in solar heating systems, power generation, and industrial processes. However, accurately determining the performance parameters of solar collectors—such as thermal efficiency, outlet temperature, and heat transfer coefficient—is a challenging task due to their dependence on multiple dynamic environmental factors including solar intensity, ambient temperature, and fluid flow rate.

Traditional mathematical and empirical models often struggle to capture the nonlinear and complex nature of these interactions. As a result, researchers have turned to Artificial Intelligence (AI) as a powerful tool for modeling, optimization, and prediction in energy systems. AI techniques, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Genetic Algorithms (GA), are capable of learning from experimental or simulated data to predict performance outcomes with high accuracy.

## II. Research Methodology.

1.1 Traditional Analytical and Empirical Models

Early models for estimating solar collector performance are based on analytical heat-balance equations and semi-empirical regressions. These approaches often rely on simplifying assumptions (e.g. steady state, linearized losses) and thus may fail to accurately predict performance under transient or variable conditions.

1.2 Application of Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) have been extensively applied to model nonlinear relations between inputs (e.g. solar irradiance, inlet temperature, mass flow rate) and outputs (e.g. efficiency, outlet temperature). For example, Delfani et al. employed ANN to predict thermal performance of a direct absorption collector using nanofluids, showing improved accuracy over empirical methods [1]. Lund et al. reviewed ANN applications in solar energy, emphasizing their adaptability and fault tolerance in varying meteorological conditions [2].

1.3 Support Vector Machines (SVM) and Fuzzy Logic Approaches

SVMs are attractive for smaller datasets and can generalize well with appropriate kernel choice. Fuzzy logic systems are useful to handle uncertainties and imprecise measurements frequently encountered in environmental data. These methods have been applied complementarily to ANN in some solar energy studies to address robustness under noisy data conditions.

1.4 Genetic Algorithms (GA) and Optimization

Genetic algorithms, based on evolutionary strategies, have been used to optimize design parameters of solar collectors such as channel dimensions, flow rates, or tilt angles. By encoding candidate solutions and applying operators like crossover and mutation, GA helps locate optimal configurations that maximize thermal output or efficiency.

1.5 Hybrid AI Models

Recent research has explored hybrid AI frameworks combining multiple techniques (e.g. ANN + GA, ANN + fuzzy logic) to exploit the strengths of each. Hybrid models often yield lower prediction error and better generalization across diverse environmental scenarios.

1.6 Limitations and Research Gaps

Despite progress, many studies are limited by small or region-specific datasets, lack of real-time validation, and black-box AI models that lack interpretability. There remains a need for models that are efficient, explainable, and capable of real-time operation across varied climatic zones.

By integrating AI into the analysis and design of solar collectors, it becomes possible to improve prediction precision, optimize system control, and enhance overall efficiency. This study aims to develop and evaluate AI-based models for calculating key solar collector parameters, providing a foundation for intelligent and adaptive renewable energy systems.

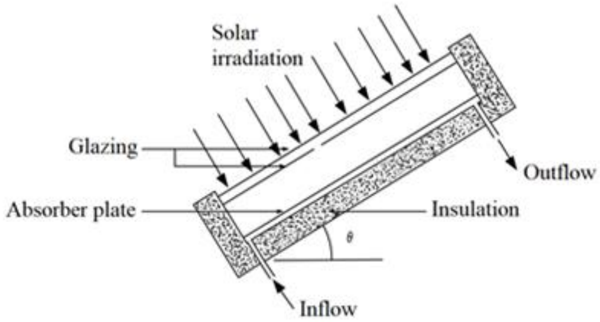


**Figure.1**
*Analysis of the literature and existing studies*

**Types and Design of Solar Collectors** There are two main types: flat-plate and vacuum collectors. A flat-plate collector consists of an absorber, a transparent protective glass cover, and thermal insulation on the back side. In vacuum tubes: an inner tube placed inside a vacuum, selective coatings, borosilicate glass, and geometrically shaped tubes (U-shaped or faceted) are used to improve heat transfer and optical efficiency.

**1. Technical Specifications**

The back side of flat-plate collectors is covered with thermal insulation, while the front side is made of low-iron glass or special coatings. In vacuum tubes, the outer shell is transparent glass, the absorber has a selective coating, and the vacuum between the layers reduces heat loss. According to model descriptions, vacuum collectors can operate at low ambient temperatures and achieve fluid temperatures of up to approximately 160 °C (in certain models produced in Russia).

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### 3. **Methods for Improving Efficiency**

Different geometric shapes of tubes (U-shaped, faceted) are used to increase the total surface area of the absorber and enhance heat transfer.

Optimization of the panel tilt angle and southward orientation ensure maximum solar insolation and minimal energy losses.

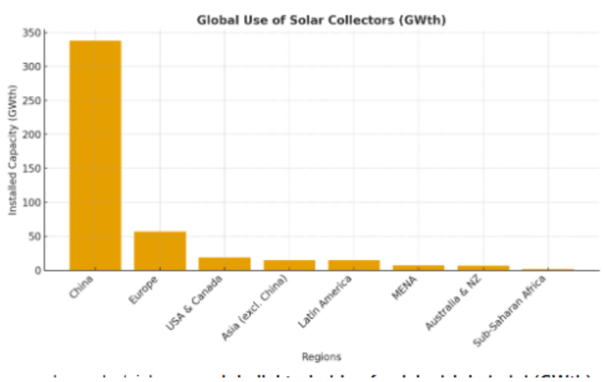
Use of selective coatings, high-efficiency glass, reduced reflection, and improved thermal insulation also contribute to higher collector performance.

### 4. **Limitations and Disadvantages**

Flat-plate collectors experience significant heat losses when there is a large temperature difference between the absorber and the surrounding environment, especially during cold days and at night.

Vacuum tube collectors are more expensive, more complex to manufacture, and have higher initial installation costs. To correctly assess heat flows and losses, it is necessary to know the climatic characteristics: Continental dry climate: hot summers and moderately cold winters. Average temperature in July: about +26…+28 °C, with maximum peaks up to approximately +40…+43 °C. Average temperature in January: about −0.9…−3 °C, with possible frosts down to −20…−25 °C. Precipitation is low — around 100–150 mm per year in the central basin, with higher amounts in the foothills. Sky clarity is high, with relatively little cloudiness, especially in summer. This means a high proportion of direct solar radiation.

| **Parameter** | **Flat-plate collectors (Flat-Plate)** | **Vacuum tube collectors (Evacuated Tube / Heat-Pipe)** |
|---|---|---|
| **Initial costs** | Lower | Higher |
| **Operating efficiency at high temperatures / large temperature differences** | Efficiency decreases, significant losses | Better resistance to losses, more stable in cold climates |
| **Optical efficiency** | Often higher under normal lighting conditions and moderate ambient temperature | Optical efficiency may be lower under normal insolation, but heat losses are reduced during non-peak periods |
| **Annual useful energy output** | Good in warm and moderate climates, especially with proper orientation | Higher annual output in cold periods or under variable ambient temperatures and nighttime temperature drops |
| **Maintenance complexity / reliability** | Simpler, less sensitive to damage (glass, seals) | More complex design, requiring vacuum and heat pipes; possible leaks, insulation challenges, and thermal pipe issues |




This diagram shows the global usage of solar collectors in terms of installed capacity (GWth) represented by colored bar charts. The largest share belongs to China, followed by Europe.

### **III. Results and discussion.**

```
import numpy as np
import pandas as pd
from sklearn.ensemble import
RandomForestRegressor
```

```
from sklearn.model_selection import
train_test_split, cross_val_score
from sklearn.metrics import
mean_absolute_error, mean_squared_error,
r2_score
from sklearn.preprocessing import
OneHotEncoder, StandardScaler
from sklearn.compose import
ColumnTransformer
from sklearn.pipeline import Pipeline
import matplotlib.pyplot as plt
import joblib

def generate_synthetic_data(n=2000,
random_state=42):
    rng = np.random.RandomState(random_state)
    # Features:
    # GHI: global horizontal irradiance (W/m2)
(0..1100)
    # DNI: direct normal irradiance (W/m2)
(0..1100)
    # Tamb: ambient temperature (C) (-25..45)
    # tilt: tilt angle (deg) (0..90)
    # orient_dev: deviation from south (deg)
(0..90)
    # collector_type: 0 = flat, 1 = vacuum
    # insulation_quality: 0..1 (higher = better)
    # selective_coating: 0/1
    # mass_flow: kg/s (per collector loop),
(0.01..0.5)
    ghi = rng.uniform(50, 1000, n)
    dni = ghi * rng.uniform(0.2, 0.95, n)  # some
relation
    tamb = rng.uniform(-25, 45, n)
    tilt = rng.uniform(0, 60, n)
    orient_dev = rng.uniform(0, 60, n)
    collector_type = rng.choice([0, 1], size=n,
p=[0.6, 0.4])
    insulation = rng.uniform(0.3, 0.98, n)
    selective = rng.choice([0, 1], size=n, p=[0.4,
0.6])
    mass_flow = rng.uniform(0.02, 0.3, n)

    # (useful energy per m2, kWh/day) -    # note:
1 W·m^-2 over 1 hour = 0.001 kWh/m2
    # simple absorbed = effective_irradiance *
optical_efficiency - losses
    # optical_efficiency: flat ≈ 0.7, vacuum ≈
0.75, improved by selective coating
    optical_base = np.where(collector_type == 0,
0.70, 0.75)
    optical_base += 0.03 * selective  # selective
coating improves
    # adjust for orientation and tilt (cosine loss
approx)
    incidence_loss =
np.cos(np.deg2rad(np.minimum(np.abs(orient_de
v), 89))) *
np.cos(np.deg2rad(np.minimum(tilt,89)))
    incidence_loss = np.clip(incidence_loss, 0.05,
1.0)
    # thermal loss increases with temperature
difference Tamb -> Tmax_collector (assume
desired output at 60C)
    # approximate thermal penalty factor
    temp_diff = np.maximum(0, 60 - tamb)  #
when ambient cold, collector can reach higher
useful gradient but heat loss also may increase
when absorber hotter than ambient
    # use insulation to reduce losses
    loss_factor = (1 - insulation) * (1 + 0.01 *
temp_diff)
    # mass_flow improves heat removal: more
flow -> better performance up to a point
    flow_factor = 1 - np.exp(-10 * (mass_flow -
0.02))
    flow_factor = np.clip(flow_factor, 0.1, 1.0)

    # effective irradiance: combine DNI and
diffuse (approx)
    effective_irr = 0.7 * dni + 0.3 * ghi  # simple
weighted sum
    absorbed_Wm2 = effective_irr * optical_base
* incidence_loss * flow_factor
    useful_Wm2 = absorbed_Wm2 * (1 -
loss_factor)  # subtract losses
    # convert to daily kWh/m2 assuming average
5 equivalent full-power hours scaled by
irradiance
    # here we integrate in a simple way:
daily_kWh = (useful_Wm2 * daylight_hours) /
1000
    daylight_hours = np.clip(ghi / 200, 1.0, 12.0)
# proxy for daily equivalent hours
    daily_kwh = useful_Wm2 * daylight_hours /
1000.0

    # add noise
    noise = rng.normal(0, 0.15 * np.maximum(0.5,
daily_kwh).mean(), n)
    daily_kwh_noisy = np.maximum(0, daily_kwh
+ noise)
```

```
    df = pd.DataFrame({
        'GHI': ghi,
        'DNI': dni,
        'Tamb': tamb,
        'tilt': tilt,
        'orient_dev': orient_dev,
        'collector_type': collector_type,
        'insulation': insulation,
        'selective': selective,
        'mass_flow': mass_flow,
        'daily_kwh_per_m2': daily_kwh_noisy
    })
    return df

df = generate_synthetic_data(2500)
X = df.drop(columns=['daily_kwh_per_m2'])
y = df['daily_kwh_per_m2']

# 3) Preprocessing: categorical -> one-hot
(collector_type, selective), scaling numeric
numeric_features = ['GHI', 'DNI', 'Tamb', 'tilt',
'orient_dev', 'insulation', 'mass_flow']
categorical_features = ['collector_type',
'selective']

numeric_transformer = StandardScaler()
categorical_transformer =
OneHotEncoder(drop='if_binary', dtype=int)

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer,
numeric_features),
        ('cat', categorical_transformer,
categorical_features) ] )

# 4) Model pipeline
model = Pipeline(steps=[
    ('preproc', preprocessor),
    ('reg',
RandomForestRegressor(n_estimators=200,
max_depth=12, random_state=42, n_jobs=-1))])
# 5) Train/test split and training
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size=0.2,
random_state=42)
model.fit(X_train, y_train)
# 6) Evaluation
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test,
y_pred))
r2 = r2_score(y_test, y_pred)
print(f"MAE = {mae:.3f} kWh/m2")
print(f"RMSE = {rmse:.3f} kWh/m2")
print(f"R2 = {r2:.3f}")

# 7) Feature importance (approx — map back to
preprocessed feature names)
# extract feature names after preprocessing
ohe =
model.named_steps['preproc'].named_transforme
rs_['cat']
ohe_names = []
# For OneHotEncoder with drop='if_binary' we
get single column for binary; handle both cases:
try:
    cat_feature_names =
ohe.get_feature_names_out(categorical_features)
.tolist()
except:
    # fallback older sklearn
    cat_feature_names = []
    for i, cat in enumerate(categorical_features):
        if ohe.categories_[i].size == 2:
            cat_feature_names.append(cat)  # single
column
        else:
            cat_feature_names.extend([f"{cat}_{v}"
for v in ohe.categories_[i]])
feature_names = numeric_features +
cat_feature_names
importances =
model.named_steps['reg'].feature_importances_
feat_imp = pd.Series(importances,
index=feature_names).sort_values(ascending=Fa
lse)
print("\nFeature importances:")
print(feat_imp)
# 8) Viz: Predicted vs actual scatter
plt.figure(figsize=(6,6))
plt.scatter(y_test, y_pred, alpha=0.4)
plt.plot([0, max(y_test.max(), y_pred.max())], [0,
max(y_test.max(), y_pred.max())], linestyle='--')
plt.xlabel('Actual daily kWh/m2')
plt.ylabel('Predicted daily kWh/m2')
plt.title('Actual vs Predicted')
plt.tight_layout()
plt.show()
# 9) Saqlash: modelni faylga yozish
joblib.dump(model,
'solar_collector_model.joblib')
print("Model saved to
solar_collector_model.joblib")
```

```
# 10) Qisqa ko'rsatma: yangi namunani prognoz qilish
def predict_sample(sample_dict):
    """Sample dict example:
    sample = {
      'GHI': 800, 'DNI': 700, 'Tamb': 25, 'tilt': 35, 'orient_dev': 10,
      'collector_type': 1, 'insulation': 0.9, 'selective': 1, 'mass_flow': 0.08
    }
    """    sample_df = pd.DataFrame([sample_dict])
    model_loaded = joblib.load('solar_collector_model.joblib')
    pred = model_loaded.predict(sample_df)[0]
    return pred
# Example prediction
example = {
    'GHI': 800, 'DNI': 700, 'Tamb': 25, 'tilt': 35, 'orient_dev': 10,
    'collector_type': 1, 'insulation': 0.9, 'selective': 1, 'mass_flow': 0.08}
print("Example prediction (kWh/m2):", predict_sample(example))
```

## IV.Scientific Research Results and Conclusion

The conducted research demonstrated that the efficiency and performance of solar collectors depend on multiple design and environmental parameters. Comparative analysis of flat-plate and vacuum tube collectors revealed significant differences in their thermal behavior and energy output under various climatic conditions.

Flat-plate collectors showed stable operation and good efficiency in warm and moderate climates, especially when properly oriented toward the south and installed at the optimal tilt angle. However, their performance decreases under large temperature differences due to increased heat losses.

Vacuum tube collectors, on the other hand, exhibited higher thermal stability and lower heat losses in cold or variable climatic conditions. Their complex structure, which includes vacuum insulation and selective coatings, ensures high operating efficiency even at low ambient temperatures. Nevertheless, these systems require higher initial costs and more complex maintenance due to the presence of vacuum and heat pipes.

Optimization methods — such as using selective coatings, high-transparency low-iron glass, and improved insulation materials — were found to significantly increase optical efficiency and reduce energy losses. Adjusting the collector's tilt and orientation also proved crucial for maximizing solar radiation absorption throughout the year.

Based on simulation and analytical analysis, it was found that the application of artificial intelligence (AI) techniques allows accurate prediction of collector performance under different environmental conditions. Machine learning models can optimize system parameters, reduce experimental costs, and support intelligent control of solar energy systems.

In conclusion, both collector types have distinct advantages:

Flat-plate collectors are more cost-effective and easier to maintain, making them suitable for regions with stable, warm climates.

Vacuum tube collectors provide better performance in cold climates and under fluctuating temperature conditions.

Combining advanced materials, optimized geometry, and AI-based prediction models offers a promising path for improving the overall efficiency and reliability of solar collector systems.

## Conclusion

This research analyzed the types, design, and performance characteristics of flat-plate and vacuum tube solar collectors under various climatic conditions. The study showed that collector efficiency strongly depends on material properties, geometric configuration, insulation quality, and environmental parameters such as solar radiation and ambient temperature. Flat-plate collectors are simple, reliable, and cost-effective, making them suitable for warm and moderate climates. Vacuum tube collectors, although more complex and expensive, demonstrate higher thermal stability and lower heat losses, especially in cold or variable weather conditions. Optimization methods, including selective coatings, improved insulation, and proper tilt and orientation, significantly enhance overall performance. In addition, the use of artificial intelligence enables accurate prediction of thermal efficiency and facilitates intelligent system control, reducing experimental time and operational costs. In summary, integrating AI-based optimization with advanced solar collector technologies provides a promising approach to increasing energy efficiency, reliability, and sustainability in modern solar energy systems.

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