Innovative Infrastructure Solutions (2025) 10:20
https://doi.org/10.1007/s41062-024-01831-9

PRACTICE-ORIENTED PAPER

Optimizing steel structures for solar panels: integrating artificial intelligence and web-based Decision support systems for enhanced efficiency and sustainability

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Received: 8 September 2024 / Accepted: 14 December 2024

Abstract

The optimization of steel structural systems for solar panel (SP) installations is crucial for improving energy efficiency and reducing costs in renewable energy systems. This study focuses on optimizing the efficiency of steel structural systems for SP using Artificial Intelligence and web-based applications. The study integrates Artificial Neural Networks (ANNs) with Finite Element Model simulations utilizing STAAD Pro V8i SS6 software and MathWorks® MATLAB® software to create effective SP support structures. The ANN model, trained on numerical analysis data from 29 sub-systems, can predict optimal design configurations with an accuracy of 97.9%. Also, the authors created A web-based decision support system (DSS) that allows users to input design criteria and retrieve optimized solutions, allowing users to input design criteria and retrieve optimized structural solutions based on location, cost, and energy output. The study identifies one-column, two-column, and four-column structural systems, comprehensively comparing energy production and structural weight. Results indicate that System C (four-column) is the most efficient in energy output, while System A (one-column) is more suited for smaller, low-cost installations. The ANN model demonstrates its ability to improve decision-making in structural design, providing practical applications for both residential and commercial installations. The findings indicate that using this web interface can significantly enhance energy output and reduce costs due to optimum weight structures in solar infrastructure. This study highlights the significant impact that ANNs can have on improving renewable energy systems by enhancing the efficiency and sustainability of future structural design advances.

Keywords Solar energy systems · Decision support system · Artificial intelligence · Steel structure systems · Sustainability · Optimization · Finite element analysis · Artificial neural networks

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Published online: 29 December 2024

Introduction and background

Solar energy is increasingly becoming a key component in the global shift toward renewable energy, particularly as the demand for clean energy rises to mitigate climate change. Steel structural systems play a pivotal role in supporting large-scale solar panel installations, and optimizing these structures is essential for maximizing energy output while minimizing costs. However, traditional methods of designing steel structures often fail to account for the complex interplay between various design variables, including weight, material strength, and environmental factors such as wind and load pressures.

One of the primary challenges in the design of solar energy systems is selecting the optimal steel structure that balances material usage, cost, and energy efficiency. With the increasing complexity of solar panel installations—ranging from small residential setups to large commercial arrays—designers must account for multiple factors that influence the system's structural integrity and energy output. Additionally, geographic location is critical, as environmental conditions such as wind loads and sunlight exposure can vary significantly.

Sustainable energy systems play a major role for renewable energy systems in combating climate change. Renewable energy systems help lower greenhouse gas emissions and promote economic growth [1]. Increasing production and improving agricultural techniques require energy, particularly RE [2], which uses solar energy and land simultaneously. Due to climate change and the need for sustainable development, the global shift to renewable energy is essential [3]. Solar Energy plays a significant role in this transition as it is a renewable resource with huge potential and the ability to scale [4]. A light steel frame building is cost-effective, structurally robust, and environmentally friendly. By 1850, cold-formed steel members were introduced into prefabricated houses during the Gold Rush of the mid-nineteenth century [5].

Furthermore, using web-based interfaces coupled with AI tools makes the design process more accessible and interactive and allows for real-time modification and optimization [4]. AI and web-based technologies are used in this study to select the optimum steel structure design for solar energy systems. Using machine learning algorithms and user-friendly interfaces [3]. A guide was introduced, outlining simplified installations and best practices, ensuring the safety and longevity of rooftop solar systems [6]. The research conducted an assessment of ultraviolet radiation's effects on plant health, explored simulation modeling for a feed pusher robot, analyzed the impact of partial shading on photovoltaic systems, identified infectious diseases in cattle facilities through theoretical studies, and examined the reliability of sectionalized electrical networks [7]. A whole-life value approach was utilized for sustainable material selection. A multi-criteria decision support system augmented decision-making. Bakhoum & Brown's DSS framework facilitated material evaluation and selection [8]. The effectiveness of two SP support structure designs, the fixed and the adjustable, was compared using Finite Element Analysis (FEA) [9]. The impact of wind loads on solar panel systems (SPS) mounted on flat roofs was investigated through a wind tunnel experiment [10]. FEA approaches were proposed to detect structural deformations and misalignments due to solar radiation, with self-weight and wind loads utilized for calculations. The method has been validated as reliable for PV system design. With the rise of photovoltaic solar panel (PVSP) technology, the design of support systems has gained prominence. PVSPs are typically mounted on steel frames, often made of aluminum, galvanized steel, painted steel, or stainless steel, and are widely used in constructing solar energy systems within structural engineering [11]. A comprehensive analysis of AI applications in photovoltaic systems emphasized efficiency and accuracy enhancements provided [12]. AI was utilized to navigate the complexities of construction projects, considering aspects like security, environment, and time [13], 14, 15, 16. The significance of web-based systems in enhancing structural design and collaborative processes was underscored, centering on Integrated Design Management for thorough project management. As participant numbers grew, a cooperative, integrated project management method became vital, presenting challenges in executing cost management throughout the design process [17]. The review of AI applications in construction focused on activity monitoring, risk management, and resource optimization alongside the successful use of robotics and machine learning. Opportunities were identified in data analytics for waste management and BIM-based models for waste reduction. Challenges were noted in AI construction applications, such as incomplete data and complexities in planning, indicating the need for further research and development [18]. Interest in utilizing AI to improve solar energy steel structures was increasing. AI and web-based interfaces were recognized as key to advancing more efficient, economical, and sustainable energy solutions. The use of AI in PV systems for optimal power tracking, energy production forecasting, and fault detection in modules or cells was increasingly observed.

Artificial neural networks (ANNs) have successfully selected steel structures. Two-dimensional steel frames can be predicted economically and safely using ANNs [19]. Additionally, Applying deep neural networks combined with Bayesian optimization has been demonstrated to achieve the best optimum structural weight for geometrically nonlinear trusses while overcoming traditional computational mechanics limitations [20]. Further, artificial neural networks offer a fast and accurate way to forecast optimum results for various structural designs using design parameters and objective functions [21].

According to the literature, steel structures for solar energy systems are increasingly being designed and implemented using AI. Renewable energy solutions are becoming more efficient, cost-effective, and sustainable due to artificial intelligence techniques and web-based interfaces. Using ANNs to select optimum ground-mounted steel structure system designs will greatly benefit structural engineering. Steel structures for solar panels present several challenges when the trend of utilizing sustainable solar energy in engineering projects increases. This results in the wrong choice of the appropriate steel structure system, increased cost, and failure to maximize steel structures. Therefore, DSS is needed. A web-based DSS is used in this study to facilitate the rapid selection of optimized designs using the ANN model. The goal is to enhance the sustainability of solar infrastructure, enhance energy production, reduce costs, and demonstrate the transformative potential of AI in the structural design of renewable Energy. The main objectives of this paper include:

- Design steel structures for SP with various dimensions to calculate weight and panel capacity.
- Utilize FEM simulations in STAAD Pro V8i SS6 to analyze load-bearing capacities, wind pressures, and material stresses.
- Develop an ANN model in MATLAB to predict the optimal structural configuration based on input variables such as weight, area, and energy output.
- Create a web-based interface for designers and engineers to evaluate energy needs and dimensions for optimal design selection of SP.
- Develop a computerized DSS to select the optimal steel structures for SP.

By addressing the challenges of structural optimization in solar energy systems, this study provides a comprehensive approach that enhances sustainability, energy efficiency, and cost-effectiveness in solar infrastructure design.

Research methodology

This research uses ANNs and web-based interfaces to select the optimal design of steel structures for solar energy systems. The methodology utilized in this study involves a combination of FEM, ANNs, and DSS to analyze and predict optimal structural configurations for solar panel installations, as shown in Fig. 1. Three primary structural configurations, system A (one-column), system B (two-column), and system C (four-column) were selected based on their relevance to various solar panel installation scenarios. Figure 1 presents a flowchart that visually outlines the research process, and the following subsection provides a detailed explanation of each step.

Finite element method (FEM) modeling: creating structural models and performing simulations

This section details the design loads, load combinations, and the codes and standards applied to devise alternative PVSP steel structural systems. The three main systems, classified into 29 sub-systems with different dimensions and spans, were utilized to simulate the solar system across fixed heights and various spans to identify the optimum design alternative.

FEA was conducted using STAAD Pro V8i SS6 to simulate the structural performance of each system, see Appendix 1. The simulations incorporated:

- Materials Definition: The materials used in this study were chosen based on their availability and relevance to steel structural systems for solar panels. Structural steel, specifically St 52, was selected for its high yield strength ($fy = 3.6$ t/cm^2) and reliability under varying load conditions.
- Load Combinations: The analysis considered dead loads (including solar panel weights and structural self-weight), live loads (100 kg), and wind loads (calculated based on wind pressures and suctions, with wind pressure values of 38.5 kg/m for the mid-section and 19.25 kg/m for the edge).
- Mesh Discretization: A mesh sensitivity analysis was performed to determine the optimal mesh size. The mesh comprised approximately 5000 elements, with finer meshing applied to critical stress points such as column connections and bracing joints.
- Load Distribution: The distributed loads were applied to simulate real-world conditions, including varying solar panel weights and wind pressures. Mid-section and edge loads were calculated and used to ensure accurate stress distribution.

Design criteria and load calculations

The materials, stresses, live loads, dead loads, and wind loads are defined according to standards such as the American Institute of Steel Construction (AISC).

- Materials & Stresses:

Fig. 1 Research methodology

  - Type of steel (e.g., St 52) with specific yield strengths ($fy = 3.6$ t/cm^2 and $fy = 5.2$ t/cm^2).
- **Loads:**

- **Live load:** 100 kg.
- **Dead load:**

    - SP weight: 23 kg.
- Distributed load (Mid): 23/2 = 11.5 kg/m.
- Distributed load (Edge): 23/4 = 5.75 kg/m.

    - **Wind load:**

- Wind Pressure (Mid): C*Q*K = 0.5*70*1.1 = 38.5 kg/m.
- Wind Pressure (Edge): C*Q*K/2 = 0.5*70*1.1/2 = 19.25 kg/m.
- Wind Suction (Mid): C*Q*K = 0.5*70*1.1 = -38.5 kg/m.
- Wind Suction (Edge): C*Q*K/2 = 0.5*70*1.1/2 = -19.25 kg/m.

SP weight variations

The number of solar panels needed depends on the building's energy use, the number of photovoltaic cells, the cell technology, and the site's sunlight exposure [22]. Table 1 compiles the average weight of solar panels by cell count, along with other key measurements and dimensions for quick reference [23].

Based on the data presented in the articles, the following was calculated:

- **Number of SPs:**

    - The area of a single SP was calculated from the data provided.
    - The area of each proposed system was calculated.
    - The area of each system was divided by the area of a single panel to determine the number of panels required.

Table 1 A summary of SP measurements and dimensions [23]

Average measurements	Residential	Commercial
Width (m)	1.0	1.0–1.1
Length (m)	1.7	1.6–1.8
Depth (m)	0.04–0.1	0.04–0.1
Solar cells (No.)	60	96
Solar cells size (m)	0.2*0.2	0.2*0.2
Area (m^2)	1.6	1.6–2.4
Weight (kg)	18.1	18.1–24.9
Energy produced (W, range)	270–440	315–550 +
Average of energy produced (W, range)	355	433

*It means (x) such as 0.2 x 0.2 (length x width)

- **Total system energy:**

    - The average Energy produced by a single SP was calculated from the data provided.
    - The average Energy was multiplied by the number of panels to determine the total system energy.

SP steel structure systems categories

System A (One column) In system A (one column), five different models were considered and divided into five distinct areas (2*3, 3*4, 4*4, 4*6 and 5*6). Table 2 specifies details regarding design elements such as columns, braces, rafters, and purlins, as well as their details. Additionally, it shows the weight per meter, the length, the weight per meter, and the total weight per meter length for each model, in addition to the weight per meter. Figures 2 show 3D models of the structure systems created from STAAD Pro V8i SS6 software.

System B (two-column) In system B (two columns), four different models were considered and divided into four different spans (3,4,5 and 6 m), as shown in Fig. 3. Then, each span was divided into areas, as shown in Table 3, which specifies details regarding design elements such as columns, braces, rafters, and purlins, as well as their details. Additionally, it shows the weight/meter, the length, and the total weight per meter length for each model.

System C (Four-column) Four span models were designed for the third system C and divided into three, four, five, and six meters, as shown in Fig. 4. Each model was divided into several different models based on their spatial configuration. Table 4 states the details related to design elements, such as columns, arches, rafters, and opposition, as well as their details. In addition to the weight per meter, there is a weight per meter and a weight per meter for each model, as well as the weight per meter and the total weight per meter for each model.

Results of FEM

Table 5 illustrates the energy generation required for each design variant, factoring in the number of systems to be energized. The summary table calculates the requisite number of solar cells for each design, derived from the stipulated area of solar cells employed in the preliminary design.

The results of the FEM simulations showed a clear distinction between the three structural systems in terms of energy production, structural weight, and cost-effectiveness. System A (one-column) was found to be the lightest but least energy-efficient, producing only 1083 W on average. This system is best suited for small-scale, low-cost

Table 2 Details of System A (One Column)

ID	Steel takeoff			System A (One column)			
	SP (Dim)	Section	Items	Profile (mm)	W/L (kg/m)	Length (m)	Weight (kg)
A1	2 m × 3 m	Sec1	Columns	Pipe 89 × 5	10.34	3	31.01
		Sec2	Purlins & Bracings	60 × 40 × 2.6RHS	3.81	23	87.56
		Sec3	Rafters	90 × 50 × 4RHS	8.15	2	16.29
					Total Weight (kg)		134.86
					Weight per meter (kg)		22.48
A2	3 m × 4 m	Sec1	Columns	Pipe 89 × 7	14.13	3	42.38
		Sec2	Bracings	60×40 × 2.6RHS	3.81	31	118.02
		Sec3	Rafters	90 × 50 × 4RHS	8.15	4	32.59
		Sec4	Purlins	50×30 × 2.6RHS	3.00	15	44.98
					Total Weight (kg)		237.96
					Weight per meter (kg)		19.83
A3	4 m × 4 m	Sec1	Columns	Pipe 108 × 6	15.06	3	45.18
		Sec2	Rafters	60×40 × 2.6RHS	3.81	30.63	116.60
		Sec3	Main Girder	90 × 50 × 4RHS	8.15	4	32.59
		Sec4	Purlins	50×30 × 2.6RHS	2.99	20	59.85
		Sec5	Bracings	60×30 × 2.6RHS	5.63	4	22.53
					Total Weight (kg)		276.75
					Weight per meter (kg)		17.30
A4	4 m × 6 m	Sec1	Columns	Pipe 133 × 6	18.75	3	56.26
		Sec2	Rafters	120×60 × 5RHS	13.08	5	65.41
		Sec3	Bracings	90 × 50 × 3.2RHS	6.61	44.84	296.49
		Sec4	Purlins	50×30 × 2.6RHS	2.99	28	83.79
					Total Weight (kg)		501.94
					Weight per meter (kg)		20.91
A5	5 m × 6 m	Sec1	Columns	Pipe 133 × 6	18.75	3	56.26
		Sec2	Rafters	140×80 × 4RHS	13.16	11	144.76
		Sec3	Bracings	90 × 50 × 3.2RHS	6.61	43.24	285.88
		Sec4	Purlins	60×40 × 2.6RHS	3.81	35	133.25
					Total Weight (kg)		620.15
					Weight per meter (kg)		20.67

installations where weight is a significant concern. System B (two-column) offered a balance between weight and energy efficiency. With an average energy production of 4330 W, this system was suitable for mid-sized installations. The cost per watt was lower than System A but higher than System C. System C (four-column), while the heaviest, produced the highest energy output of up to 11,547 W. Despite its higher initial cost, this system proved to be the most cost-effective in terms of long-term energy production. It is recommended for large-scale commercial installations with high space and energy demands.

A cost analysis was performed, comparing the initial investment of each system to the energy produced. System A had the lowest initial cost but the highest cost per watt of energy produced. Despite having a higher initial cost due to its weight, System C had the lowest cost per watt over time, making it the most economical option for high-energy installations.

According to the data analysis in Table 5, several key insights can be drawn regarding the performance of different steel structural systems for solar panels. The findings focus on each system configuration's energy production, structural weight, and area utilization.

- *System C (Four-Column):*
  - System C consistently produced the highest energy output compared to its structural weight. For example, in the 6 m × 8 m configuration, System C generated 11,547 W of energy while weighing 1142.8 kg. This corresponds to an energy output

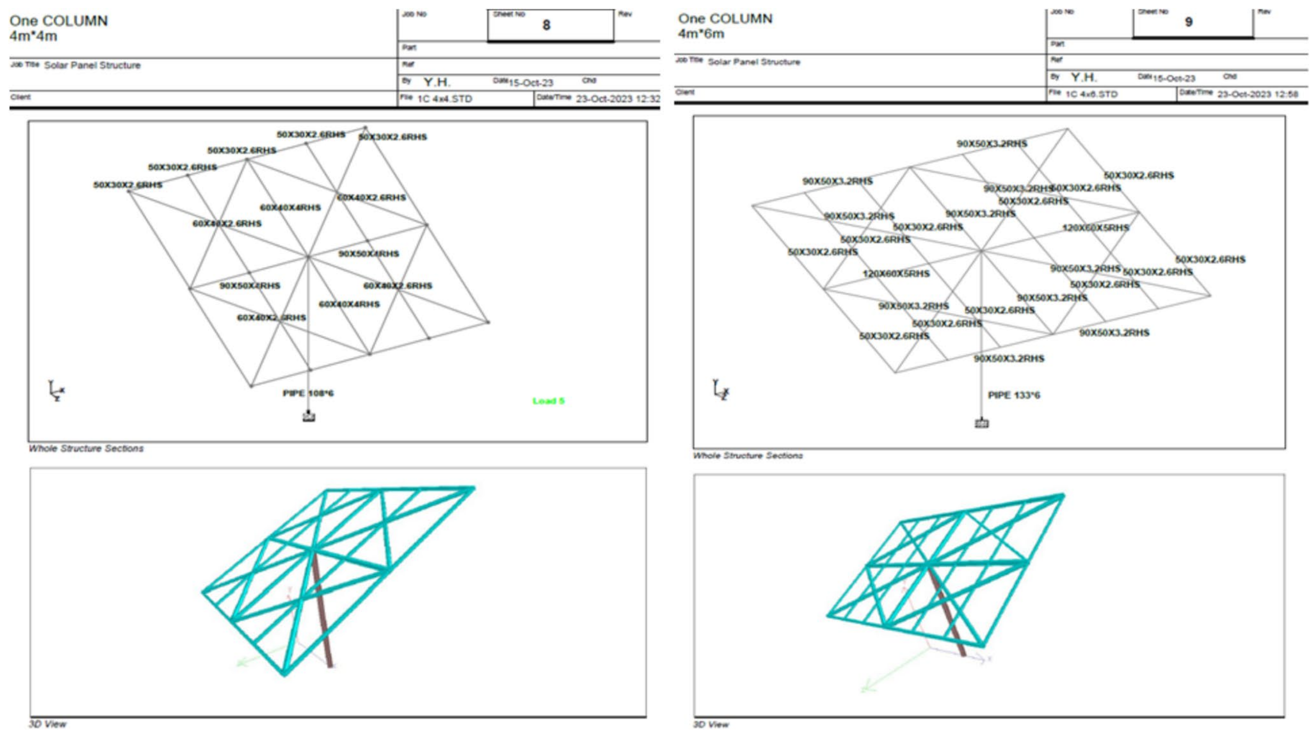


Fig. 2 Example of (4 m*4 m / 4 m*6 m) of 2D and 3D of one column system

of approximately 10.1 W per kilogram, the highest among all systems.

- System C is particularly suited for large-scale commercial installations where maximizing energy output is critical and weight is less of a constraint. Its larger area capacity allows for more solar panels, increasing energy production.

- *System A (One-Column):*

  - System A had the lightest overall weight across all configurations but produced lower energy than System B and C. For instance, the 2 m × 3 m configuration of System A weighed 134.86 kg and generated 1083 W, yielding an energy output of 8.03 W per kilogram. This system is optimal for smaller, low-cost installations where weight reduction is a priority over energy output.
  - Due to its lighter weight, System A is more suitable for small-scale residential installations where structural weight limitations are important, but the energy demand is not as high.

- *System B (Two-Column):*

  - System B offers a good balance between weight and energy output, making it suitable for mid-sized installations. In the 4 m × 6 m configuration, System B produced 4330 W of energy while weighing 390.74 kg, resulting in an energy output of approximately 11.08 W per kilogram. This system provides a compromise between the lightweight design of System A and the high energy output of System C.
  - System B is optimal for installations where a balance between structural weight and energy output is desired, making it a versatile option for various applications.

- *Weight-to-Energy Ratio Comparison:*

  - System C (Four-Column) had the highest energy output relative to weight, making it the most efficient energy production per kilogram of structure.
  - System A (One-Column) had the lowest energy-to-weight ratio but remains the best choice for installations where reducing the overall structural weight is a priority.
  - System B (Two-Column) balanced weight and energy output, making it a versatile option for mid-sized installations.

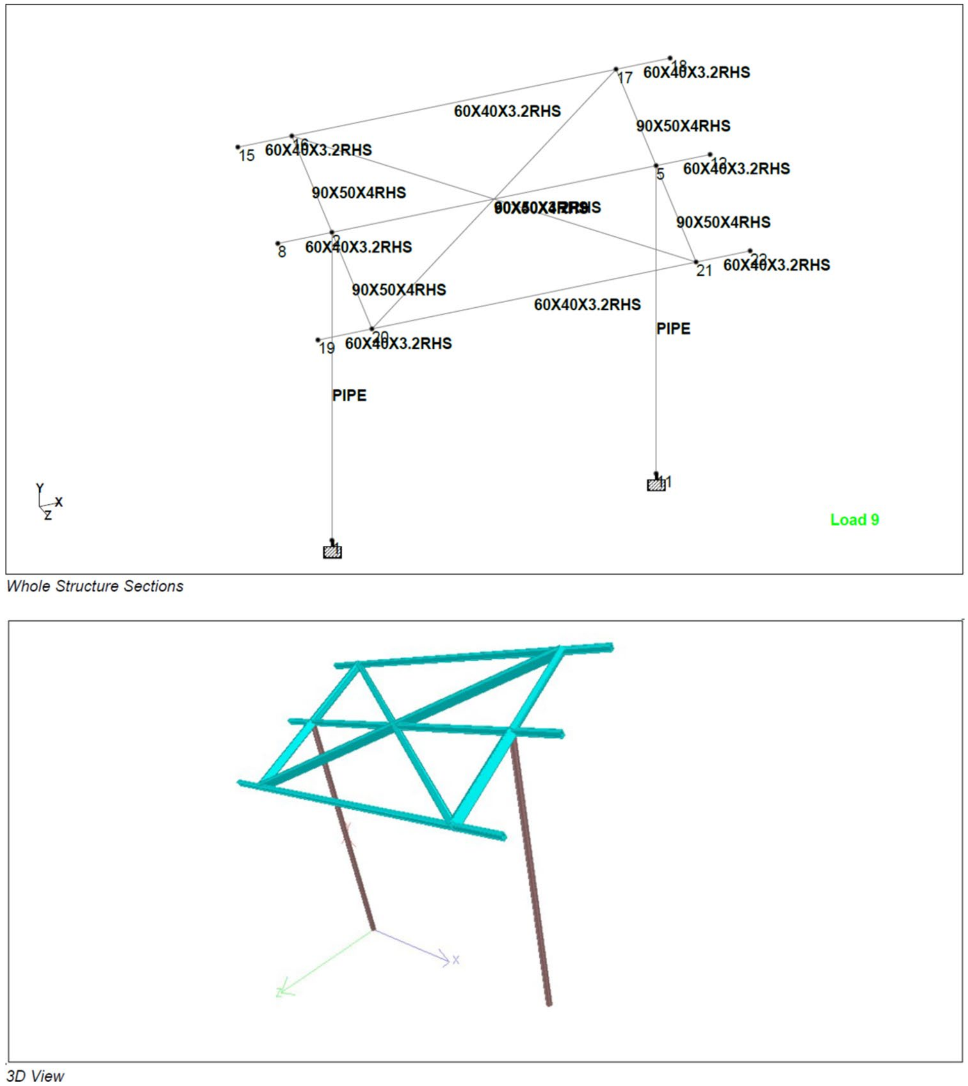


Fig. 3. 2D and 3D examples of 3 m/4 m span of two-column system details

Development of ANN Model: developing and training the ANN for prediction and optimization

The database obtained from the structural analysis is used to train the ANN model. Based on the input parameters, an ANN model was developed to predict structural systems, total energy production, the number of solar panels, and total weight, as shown in Table 6.

The steps for developing the ANN's model for this study are as follows:

The architecture of the ANN model was implemented using MathWorks® MATLAB® software, as shown in Fig. 5, with the following steps, as shown in Fig. 6:

The inputs: The inputs are identified as the main variables affecting the outputs of these neural networks. These inputs are as follows:

- Input 1 (X_1): No of Columns (ranging from 1 to 4 columns depending on the system).
- Input 2 (X_2): Span of each sub-system (29) in meters (0, 3, 4, 5, 6.3, 4, 5, 6 m).
- Input 3 (X_3): Area in square meters (6–64 m^2).

There are constants, such as fixed height = 3 m, average production energy of solar panel = 433 watts, and area of solar panel = 2.4 m^2).

The outputs: The outputs that represent the required target to be determined by the artificial.

neural networks are as follows:

- Output 1 (Y_1): Weight of each sub-system in kg.
- Output 2 (Y_2): Number of solar systems of each sub-system.

Table 3 Details of System B (Two Columns)

ID		Steel takeoff		System B (Two columns)					
		Span	SP (Dim)	section	Items	Profile (mm)	W/L (kg/m)	Length (m)	Weight (kg)
B1	B1.1	3 m	2 m × 4 m	Sec1	Columns	Pipe 60 × 5	6.77	6	40.605
				Sec2	Purlins	60 × 40 × 3.2RHS	4.31	11.21	48.363
				Sec3	Rafters & Bracings	90 × 50 × 4RHS	7.94	11.5	91.334
							Total Weight (kg)		180.30
							Weight per meter (kg)		22.54
	B1.2		4 m × 4 m	Sec1	Columns	Pipe 89 × 4	8.37	6	50.203
				Sec2	Purlins	60 × 40 × 3.2RHS	4.61	20	92.121
				Sec3	Rafters & Bracings	90 × 50 × 4RHS	8.15	22.42	182.667
							Total Weight (kg)		324.99
							Weight per meter (kg)		20.31
	B1.3		4 m × 6 m	Sec1	Columns	Pipe 89 × 6	12.26	6	73.533
				Sec2	Purlins	60 × 40 × 4RHS	5.63	30	168.966
				Sec3	Rafters & Bracings	90 × 50 × 3.2RHS	6.61	22.42	148.242
							Total Weight (kg)		390.74
							Weight per meter (kg)		16.28
B2	B2.1	4 m	4 m × 4 m	Sec1	Columns	Pipe 60 × 5	8.37	6	50.20
				Sec2	Purlins	80 × 40 × 3.2RHS	5.61	20	112.17
				Sec3	Rafters & Bracings	90 × 50 × 3.2RHS	6.61	25.89	171.16
							Total Weight (kg)		333.54
							Weight per meter (kg)		20.85
	B2.2		4 m × 6 m	Sec1	Columns	Pipe 89 × 6	12.26	6	73.53
				Sec2	Purlins	90 × 50 × 3.2RHS	6.61	30	198.34
				Sec3	Rafs & Bracings	100 × 60 × 3.2RHS	7.61	25.89	197.12
							Total Weight (kg)		468.99
							Weight per meter (kg)		19.54
	B2.3		6 m × 6 m	Sec1	Columns	Pipe 108 × 6	15.06	6	90.37
				Sec2	Purlins	90 × 50 × 3.2RHS	6.61	26	171.90
				Sec3	Rafs&Bracings	120 × 60 × 4RHS	10.65	34.83	371.09
							Total Weight (kg)		633.35
							Weight per meter (kg)		17.59
B3	B3.1	5 m	4 m × 6 m	Sec1	Columns	Pipe 87 × 7	14.13	6	84.76
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	30	114.21
				Sec3	Bracings	80 × 40 × 3.2RHS	5.61	34.61	194.13
				Sec4	Raftars	90 × 50 × 3.2RHS	6.61	8	52.89
							Total Weight (kg)		445.99
							Weight per meter (kg)		18.58
	B3.2		6 m × 6 m	Sec1	Columns	Pipe 108 × 7	17.40	6	104.39
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	42	159.90
				Sec3	Bracings	90 × 50 × 3.2RHS	6.61	42.24	279.27
				Sec4	Raftars	120 × 60 × 4RHS	10.65	12	127.84
							Total Weight (kg)		671.40
							Weight per meter (kg)		18.65
	B3.3		6 m × 8 m	Sec1	Columns	Pipe 108 × 8	19.69	6	118.13
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	56	213.19
				Sec3	Bracings	90 × 50 × 3.2RHS	6.61	42.24	279.27
				Sec4	Raftars	120 × 80 × 4RHS	11.91	12	142.88
							Total Weight (kg)		803.47
							Weight per meter (kg)		16.74

Table 3 (continued)

ID		Steel takeoff		System B (Two columns)					
		Span	SP (Dim)	section	Items	Profile (mm)	W/L (kg/m)	Length (m)	Weight (kg)
	B4.1	6 m	6 m × 6 m	Sec1	Columns	Pipe 108 × 7	17.40	6	104.39
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	42	159.90
				Sec3	Bracings	100 × 60 × 3.2RHS	7.61	45.94	349.80
				Sec4	Raftars	120 × 60 × 4RHS	10.65	12	127.84
							Total Weight (kg)		741.93
							Weight per meter (kg)		20.61
	B4.2		6 m × 8 m	Sec1	Columns	Pipe 133 × 6	18.75	6	112.51
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	58	220.81
				Sec3	Bracings	100 × 60 × 3.2RHS	7.61	39.94	304.11
				Sec4	Raftars	120 × 80 × 4RHS	11.91	18	214.32
							Total Weight (kg)		851.76
							Weight per meter (kg)		17.74
s	B4.3		8 m × 8 m	Sec1	Columns	Pipe 133 × 8	24.61	6	147.66
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	72	274.15
				Sec3	Bracings	120 × 80 × 4RHS	11.91	54	642.96
				Sec4	Raftars	150 × 100 × 4RHS	15.04	16	240.64
							Total Weight (kg)		1305.41
							Weight per meter (kg)		20.40

- Output 3 (Y_3): Total production energy of each sub-system in watts.

Training and Validation: The model was trained on the data and validated to ensure accurate predictions; the model uses 70% for training, 15% for validation, and 15% for testing.

R-values (correlation coefficients) are statistical measures that describe "the strength and direction of a linear relationship between two variables" [24]. In regression analysis, the R-value (often represented as R or R^2) provides insights into how well the independent variable (s) predict the dependent variable [25]. "Regression R-values quantify the correlation between the actual and predicted values of the dependent variable. The strength of the relationship" [26–28]:

- "0–0.3: Weak correlation.
- 0.3–0.5: Moderate correlation.
- 0.5–0.7: Strong correlation.
- 0.7–1.0: Very strong correlation".

In this study, the fit is quite good across all data sets, with R-values of 0.979 for steel structure systems of solar energy, as shown in Fig. 7. These R-values indicate:

- R-value (0.979) is close to 1, suggesting a strong positive correlation between the actual and predicted values of the dependent variable.
- This suggests that the regression model can accurately predict the dependent variable using the independent variables and that the model fits the data well.
- The high R-value demonstrates that the independent variables account for a significant portion of the variance in the dependent variable.
- The R-value suggests that the models effectively capture the underlying patterns in the data for structural systems.

The error histograms for structure systems of solar Energy indicate the distribution of prediction errors made by the ANN model. The histograms help understand the model's accuracy and areas where predictions may deviate from actual values, as shown in Fig. 8. Steel structure systems: The error histogram shows that most prediction errors are centered around zero, indicating good model accuracy.

The higher errors seen in Fig. 8, particularly at − 148.1 and 170.8, are due to several factors related to the input data's complexity and the ANN model's inherent limitations in predicting specific structural configurations. These errors may be caused by:

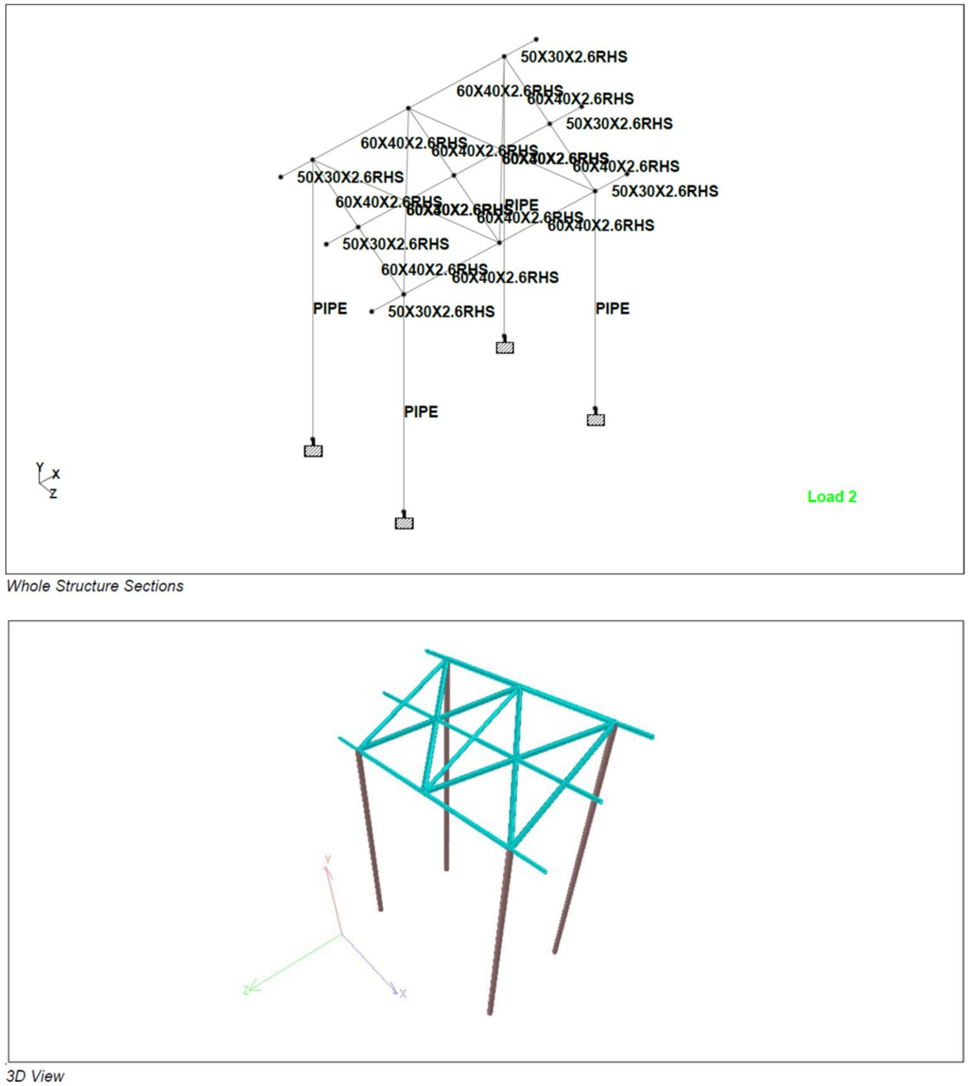


Fig. 4. 2D and 3D examples of a 3 m span of 4-column system details

- Specific structural configurations, especially those with extreme span or area values, may deviate significantly from the average patterns observed in the data. These outliers can lead to higher prediction errors, as the ANN model is more likely to struggle with configurations far from the training data's typical range.
- For some configurations, particularly those with larger spans or more complex load distributions (e.g., System C with four columns), the FEM simulations may produce results that are harder to predict accurately using the ANN model. This complexity can introduce higher prediction errors for these configurations.
- Errors can also arise from mesh sensitivity in the FEM model. In some areas of the structure, particularly around joints or where stress concentrations occur, even small variations in mesh density can lead to differences in stress and deformation predictions, contributing to higher error values.

High R-value enhances the confidence in the model's predictions, making it a valuable tool for practical applications such as structural analysis and design optimization. Engineers and decision-makers can use these models to make informed decisions about structure systems of solar energy design, maintenance, and performance evaluation, relying on the robustness of the high R-values. While high R-values are desirable, assessing other aspects of model performance, such as residual analysis and potential overfitting, is important to ensure the model's generalizability. R-values are crucial indicators of the strength and direction of the relationship between variables in regression analysis (Fig. 9).

The ANN model plays a critical role in optimizing the design of steel structures for solar panel installations. Based on the data collected from 29 sub-systems, the ANN was trained to predict three essential outputs:

Table 4 Details of System C (Four Columns)

ID		Steel Takeoff			System C (Four columns)				
		Span	SP (Dim)	Section	Items	Profile (mm)	W/L (kg/m)	Length (m)	Weight (kg)
C1	C1.1	3 m	2 m × 4 m	Sec1	Columns	Pipe 60 × 5	7.09	12	85.05
				Sec2	Purlins	50 × 30 × 2.6RHS	2.99	12	35.91
				Sec3	Rafs&Bracings	60 × 40 × 2.6RHS	3.81	22	83.76
							Total Weight (kg)		204.71
							Weight per meter (kg)		25.59
	C1.2		4 m × 4 m	Sec1	Columns	Pipe 76 × 4	7.09	12	85.05
				Sec2	Purlins	50 × 30 × 2.6RHS	2.99	20	59.85
				Sec3	Bracings	60 × 40 × 2.6RHS	3.81	30	114.21
				Sec4	Rafters	90 × 50 × 4RHS	2.99	14	41.89
							Total Weight (kg)		301.00
							Weight per meter (kg)		18.81
	C1.3		4 m × 6 m	Sec1	Columns	Pipe 76 × 4	7.09	12	85.05
				Sec2	Purlins	50 × 30 × 2.6RHS	2.99	28	83.79
				Sec3	Bracings	60 × 40 × 2.6RHS	3.81	42	159.90
				Sec4	Rafters	80 × 40 × 3.2RHS	5.61	12	67.31
							Total Weight (kg)		396.04
							Weight per meter (kg)		16.50
C2	C2.1	4 m	4 m × 4 m	Sec1	Columns	Pipe 76 × 4	7.09	12	85.05
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	20	76.14
				Sec3	Bracings	60 × 40 × 3.2RHS	4.61	34.63	159.50
				Sec4	Rafters	80 × 40 × 3.2RHS	5.61	8	44.87
							Total Weight (kg)		365.56
							Weight per meter (kg)		22.85
	C2.2		4 m × 6 m	Sec1	Columns	Pipe 76 × 4	7.09	12	85.05
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	30	114.21
				Sec3	Bracings	60 × 40 × 3.2RHS	4.61	34.63	159.50
				Sec4	Rafters	90 × 50 × 3.2RHS	6.62	8	52.98
							Total Weight (kg)		411.74
							Weight per meter (kg)		17.16
	C2.3		6 m × 6 m’	Sec1	Columns	Pipe 76 × 5	8.74	12	104.84
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	42	159.90
				Sec3	Bracings	90 × 50 × 3.2RHS	6.61	46.84	309.71
				Sec4	Rafters	100 × 60 × 3.2RHS	7.61	12	91.37
							Total Weight (kg)		665.80
							Weight per meter (kg)		18.49

Table 4 (continued)

ID		Steel Takeoff			System C (Four columns)				
		Span	SP (Dim)	Section	Items	Profile (mm)	W/L (kg/m)	Length (m)	Weight (kg)
C3	C3.1	5 m	4 m × 6 m	Sec1	Columns	Pipe 76 × 4	7.09	12	85.05
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	25	95.18
				Sec3	Rafs&Bracings	80 × 40 × 3.2RHS	5.61	52.61	295.09
							Total Weight (kg)		475.31
							Weight per meter (kg)		19.80
	C3.2		6 m × 6 m	Sec1	Columns	Pipe 89 × 5	10.34	12	124.03
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	36	137.05
				Sec3	Bracings	90 × 50 × 3.2RHS	6.61	52.24	345.38
				Sec4	Rafters	100 × 60 × 3.2RHS	7.61	12.5	95.18
							Total Weight (kg)		701.64
							Weight per meter (kg)		19.49
	C3.3		6 m × 8 m	Sec1	Columns	Pipe 89 × 5	10.34	12	124.03
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	48	182.74
				Sec3	Bracings	90 × 50 × 3.2RHS	6.61	67.05	443.27
				Sec4	Rafters	100 × 60 × 4RHS	7.61	16.5	125.63
							Total Weight (kg)		875.67
							Weight per meter (kg)		18.24
C4	C4.1	6 m	6 m × 6 m	Sec1	Columns	Pipe 89 × 5	10.34	12	124.03
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	42	159.90
				Sec3	Rafs&Bracings	100 × 60 × 3.2RHS	7.61	69.94	532.53
							Total Weight (kg)		816.46
							Weight per meter (kg)		22.68
	C4.2		6 m × 8 m	Sec1	Columns	Pipe 89 × 6	12.26	12	147.07
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	56	213.19
				Sec3	Bracings	100 × 60 × 3.2RHS	7.61	57.94	441.17
				Sec4	Rafters	100 × 60 × 4RHS	12.26	12	147.07
							Total Weight (kg)		948.49
							Weight per meter (kg)		19.76
	C4.3		8m × 8m	Sec1	Columns	Pipe 108 × 5	12.67	12	152.09
				Sec2	Purlins	60 × 40 × 2.6RHS	3.81	72	274.11
				Sec3	Bracings	100 × 60 × 3.2RHS	7.61	74.36	566.21
				Sec4	Rafters	100 × 60 × 4RHS	9.40	16	150.40
							Total Weight (kg)		1142.80
							Weight per meter (kg)		17.86

- Total Weight of the Structure: The weight is a crucial factor in determining the cost and material usage for different configurations.
- Number of Solar Panels: This determines the total area covered by solar panels and the energy they can generate.
- Total Energy Production: The predicted energy output measures the system's efficiency.

The model achieved high accuracy, with an R-value of 0.979, indicating a very strong correlation between the actual and predicted values for all three outputs. This means the ANN can be relied upon to provide optimal configurations for different solar energy needs, making it a valuable tool for engineers and designers.

Furthermore, the ANN model is significant because it automates a complex process that would otherwise require

Table 5 Summary of all structural systems dimensions, weight, and power calculations

No	ID		Span	Dimensions (m)		Area (m^2)	Weight (Kg)	W/A (Kg/m^2)	Area of SP	No. of SP	Average energy produced of SP (Watt)	Total energy production (Watt)
				a	b							
System A	A	A1	0	2	3	6	134.86	22.48	2.4	3	433	1083
		A2		3	4	12	237.87	19.82		5		2165
		A3		4	4	16	276.75	17.3		7		2887
		A4		4	6	24	501.94	20.91		10		4330
		A5		5	6	30	620.15	20.67		13		5413
System B	B1	B1.1	3 m	2	4	8	180.3	22.54		3		1443
		B1.2		4	4	16	313.48	20.31		7		2887
		B1.3		4	6	24	390.74	16.28		10		4330
	B2	B2.1	4 m	4	4	16	333.54	20.85		7		2887
		B2.2		4	6	24	468.99	19.54		10		4330
		B2.3		6	6	36	633.35	17.59		15		6495
	B3	B3.1	5 m	4	6	24	445.99	18.58		10		4330
		B3.2		6	6	36	671.4	18.65		15		6495
		B3.3		6	8	48	803.47	16.74		20		8660
	B4	B4.1	6 m	6	6	36	741.92	20.61		15		6495
		B4.2		6	8	48	821.3	17.11		20		8660
		B4.3		8	8	64	1305.41	20.4		27		11,547
System C	C1	C1.1	3 m	2	4	8	204.71	25.59		3		1443
		C1.2		4	4	16	301	18.81		7		2887
		C1.3		4	6	24	396.21	16.51		10		4330
	C2	C2.1	4 m	4	4	16	365.73	22.86		7		2887
		C2.2		4	6	24	411.74	17.16		10		4330
		C2.3		6	6	36	665.8	18.49		15		6495
	C3	C3.1	5 m	4	6	24	475.31	19.8		10		4330
		C3.2		6	6	36	701.64	19.49		15		6495
		C3.3		6	8	48	875.67	18.24		20		8660
	C4	C4.1	6 m	6	6	36	816.46	22.68		15		6495
		C4.2		6	8	48	948.49	19.76		20		8660
		C4.3		8	8	64	1142.8	17.86		27		11,547

Table 6 Input and output for the ANNs model

No. of Columns	Span (m)	Area (m^2)	Weight (Kg)	No. of SP	Total Energy Production (watt)
1	0	6	134.86	3	1083
1	0	12	237.87	5	2165
1	0	16	276.75	7	2887
1	0	24	501.94	10	4330
1	0	30	620.15	13	5413
2	3	8	180.3	3	1443
2	3	16	313.48	7	2887
2	3	24	390.74	10	4330
2	4	16	333.54	7	2887
2	4	24	468.99	10	4330
2	4	36	633.35	15	6495
2	5	24	445.99	10	4330
2	5	36	671.4	15	6495
2	5	48	803.47	20	8660
2	6	36	741.92	15	6495
2	6	48	821.3	20	8660
2	6	64	1305.41	27	11,547
4	3	8	204.71	3	1443
4	3	16	301	7	2887
4	3	24	396.21	10	4330
4	4	16	365.73	7	2887
4	4	24	411.74	10	4330
4	4	36	665.8	15	6495
4	5	24	475.31	10	4330
4	5	36	701.64	15	6495
4	5	48	875.67	20	8660
4	6	36	816.46	15	6495
4	6	48	948.49	20	8660
4	6	64	1142.8	27	11,547

extensive manual simulation and analysis. By reducing the time and effort needed for design optimization, the ANN model enhances efficiency, reduces costs, and ensures that solar energy systems are structurally sound and efficient.

Web-based decision support system (DSS)

The Web-Based DSS was developed to provide engineers, architects, and decision-makers with an efficient tool for optimizing solar energy production and the structural design of solar panel support systems. The DSS is designed to simplify the complex process of selecting the most suitable structural configuration by allowing users to input key project parameters, such as available area and required energy output, and receive tailored recommendations for the best design options. The primary benefits of the DSS include:

- Users can quickly obtain optimized design solutions without manually conducting numerous FEM simulations or trial-and-error calculations.
- The DSS ranks different structural systems (e.g., one-column, two-column, and four-column designs) based on energy efficiency, structural weight, and area utilization, helping users select the most cost-effective and energy-efficient solution for their specific project.
- The system is highly flexible, allowing users to adjust input parameters to match specific project needs, whether for residential installations or large commercial projects.

Optimal solar energy production is achieved by designing efficient structures, evaluating all alternatives, and using a web application that guides users to the best energy solutions, as shown in Fig. 10.

The system presented the best alternatives, sorted from the smallest/lowest to the largest/highest area by default. Using the energy or weight sorting buttons instead of the column sort on the table in Fig. 11 will apply the sort to all the available alternatives, not only the selected number of alternatives. This can help users quickly identify the best options instead of manually sorting them individually. Furthermore, it can also help to save time when sorting large amounts of data.

- 1st step: Area required: Indicates the available floor area (m^2).

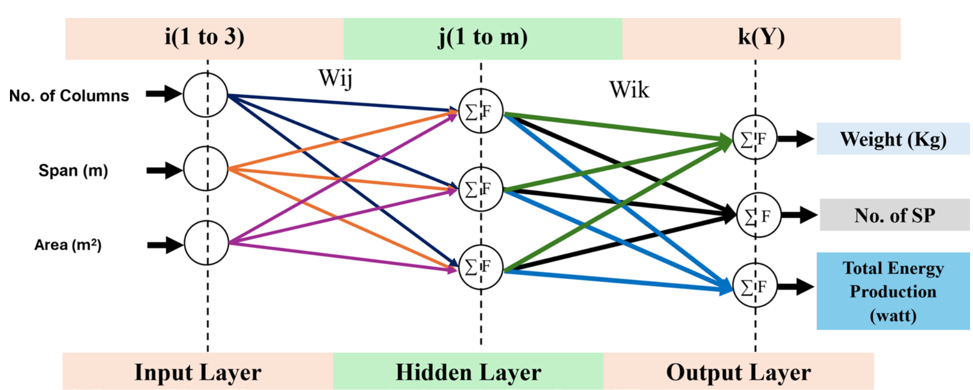
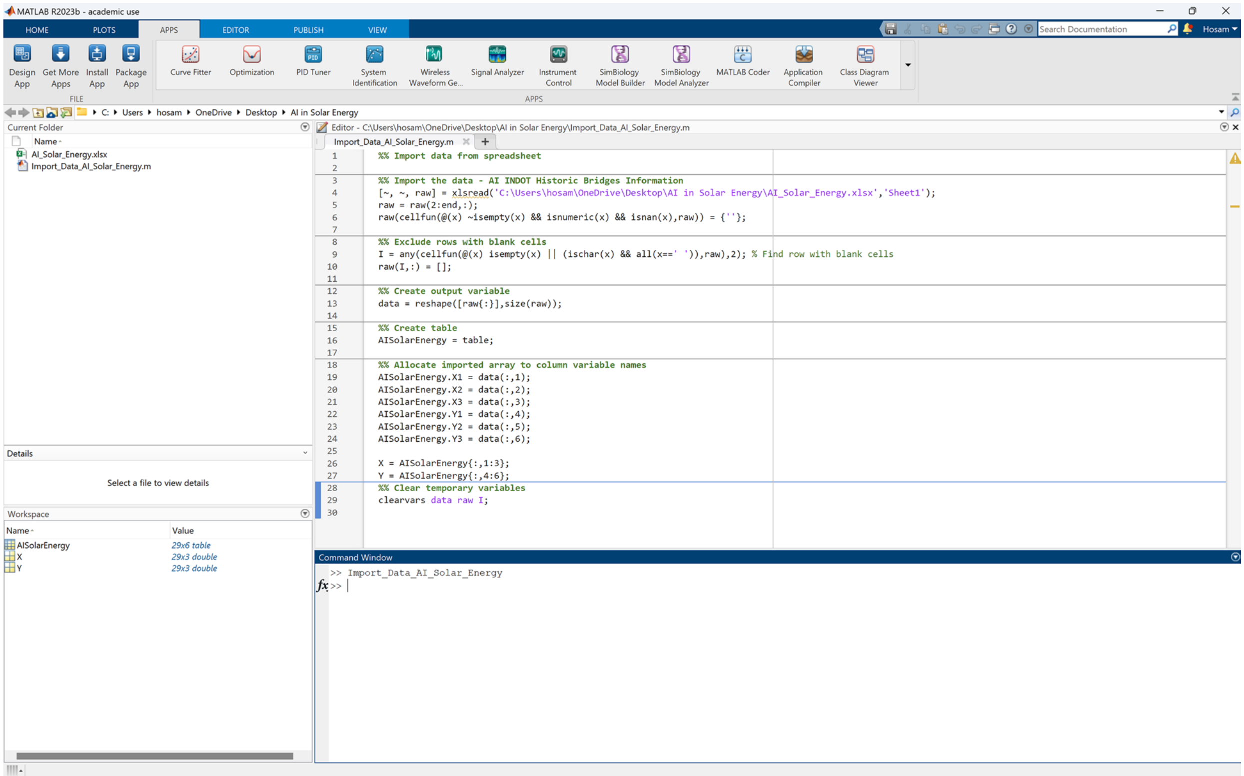
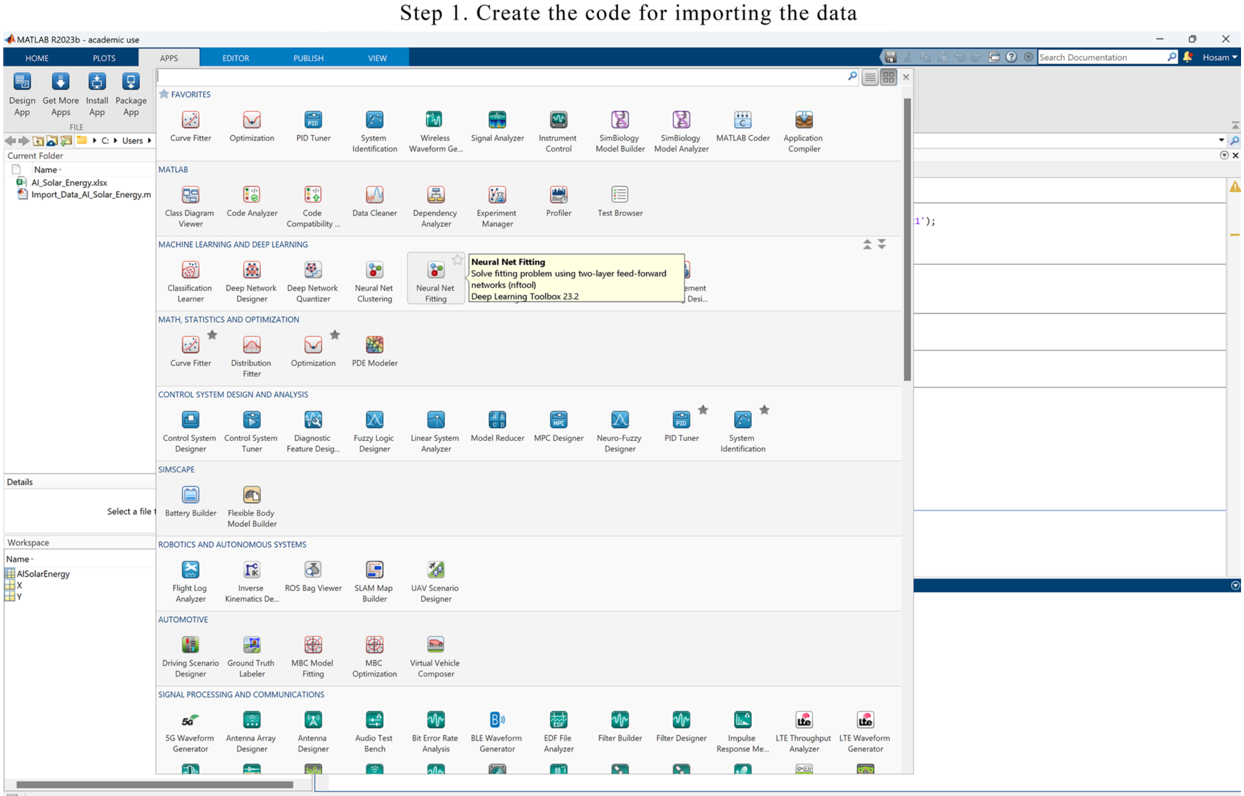


Fig. 5 Architecture of ANN model for solar panel structure systems

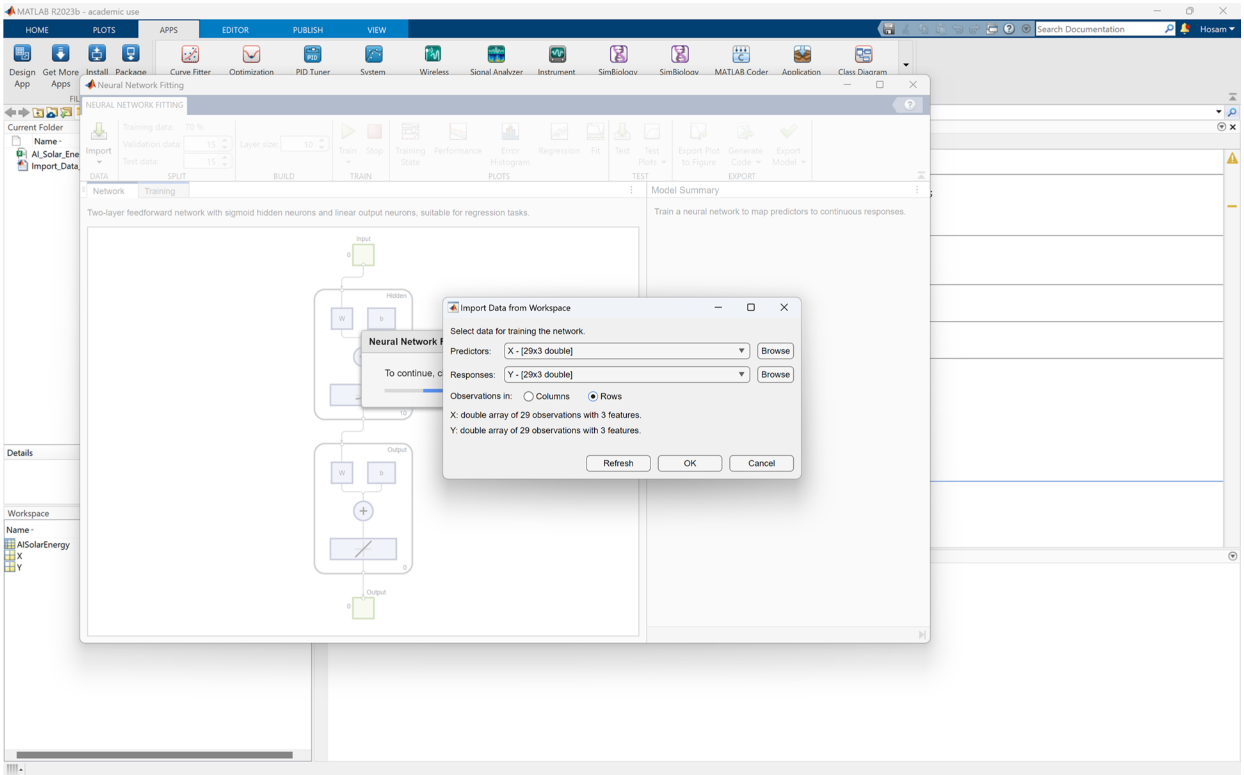


Step 1. Create the code for importing the data

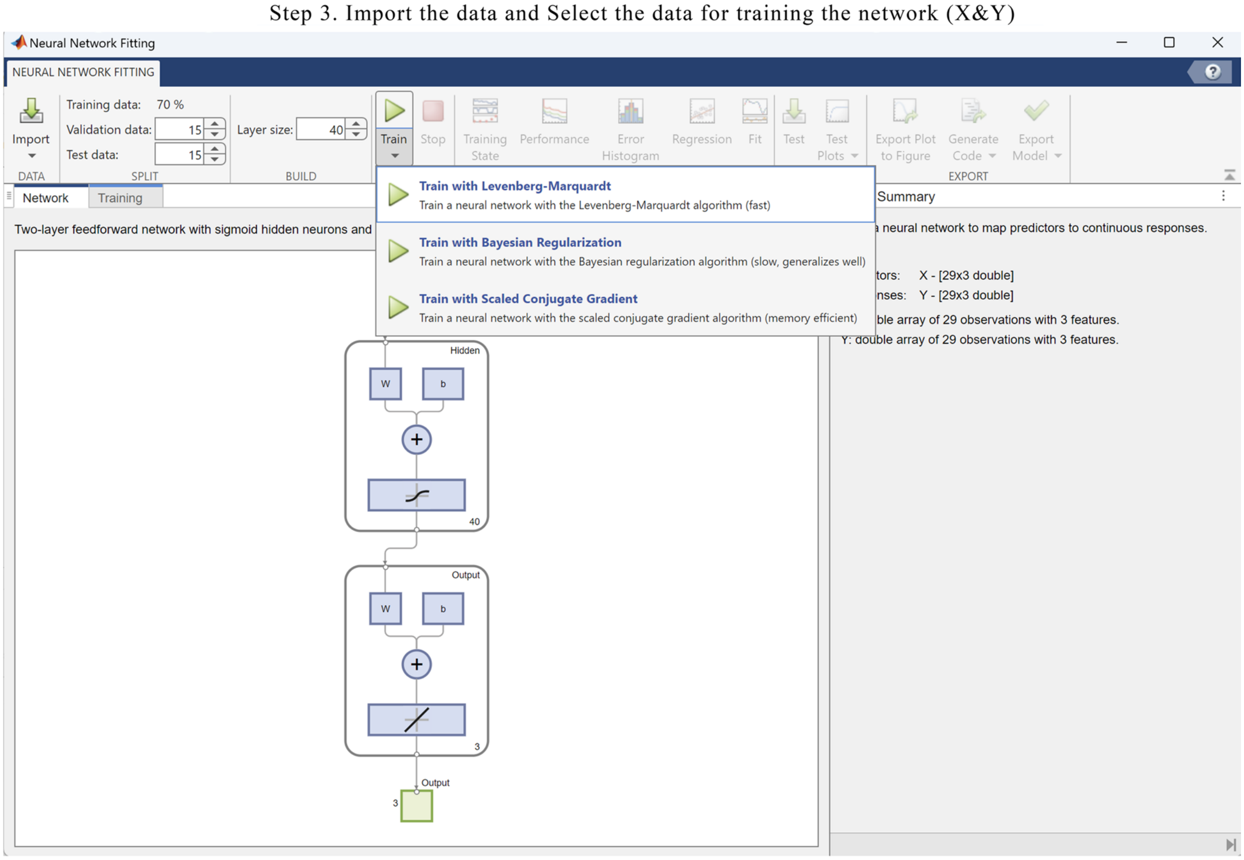


Step 2. Select Neural Net Fitting

Fig. 6 Steps of the ANN in the MathWorks® MATLAB® software



Step 3. Import the data and Select the data for training the network (X&Y)



Step 4. Select the training data 70%, validation data 15%, test data 15%, and layer size 40% - then Train with Levenberg-Marquardt

Fig. 6 (continued)

Fig. 7 R-Value for the data

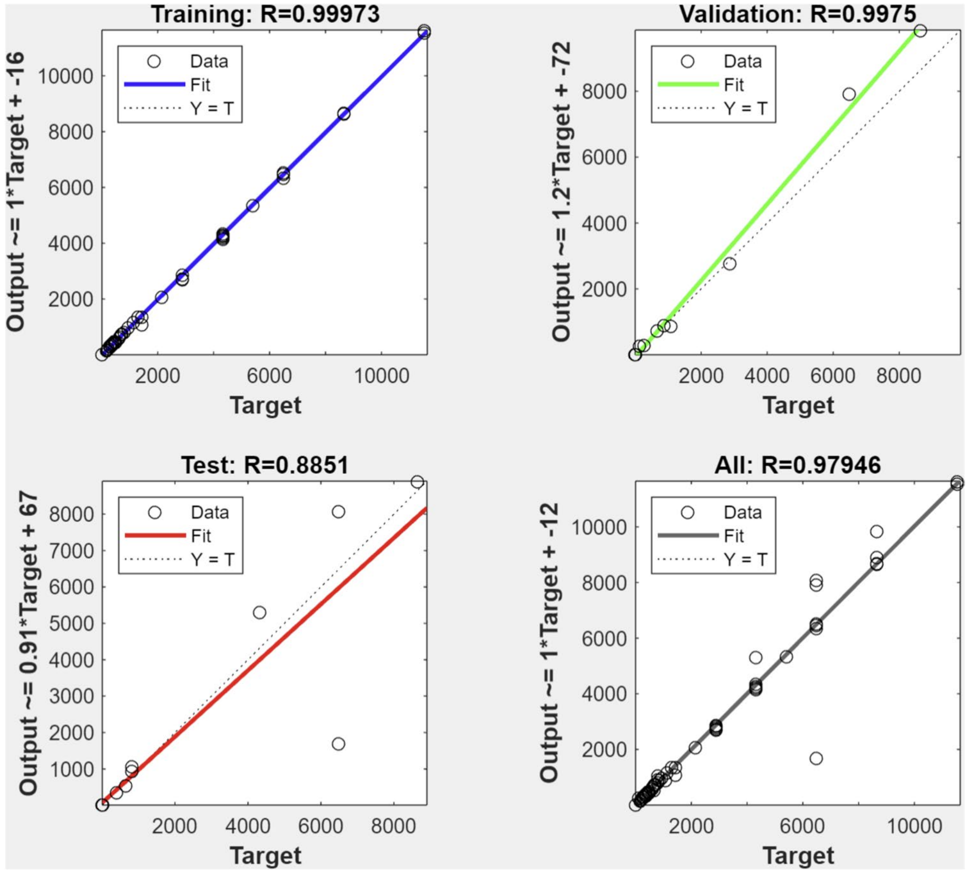
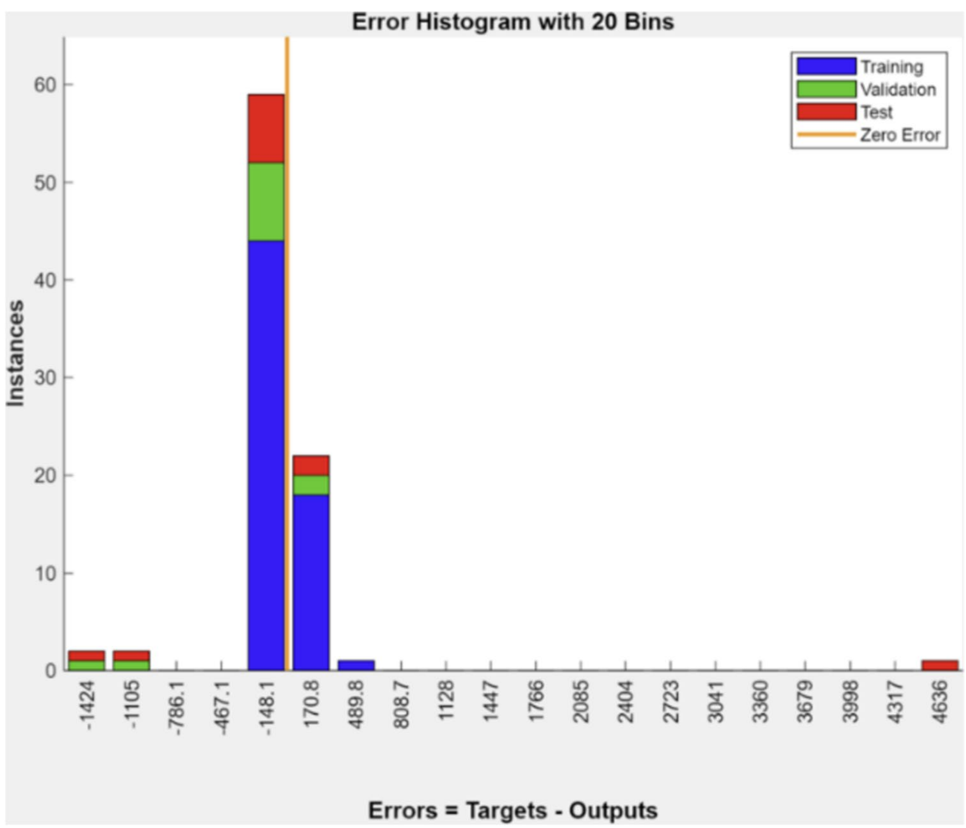


Fig. 8 Error Histogram for the data



```
% ===== SIMULATION ========

% Dimensions
Q = size(x1,1); % samples

% Input 1
x1 = x1';
xp1 = mapminmax_apply(x1,x1_step1);

% Layer 1
a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*xp1);

% Layer 2
a2 = repmat(b2,1,Q) + LW2_1*a1;

% Output 1
y1 = mapminmax_reverse(a2,y1_step1);
y1 = y1';
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

Fig. 9 The final results of the ANN model (Simulation and Module Functions)

- 2nd step: Energy amount required: Specify the power required (in Watts).
- 3rd step: Number of alternatives: The default is three, but the user may select any number (more or less than 3).
- 4th step: Name, IDs, and physical dimensions of the model.
- 5th step: A weight per unit
- 6th step: Number of SPs required and the amount of solar energy output
- 7th step: Numbers of structure systems and total area column; it can be sorted as ascending or descending.
- 8th step: Total energy column; it can be sorted as ascending or descending
- 9th step: Areas equal to or smaller than the required area but none larger. Energy was displayed equal to or higher than the required amount, but none was less.

The DSS was designed to allow users to input specific criteria, such as available area and required energy output, and receive recommendations for optimal structural configurations. The DSS ranked the available configurations based on energy output, weight, and cost, providing users with a clear decision-making tool. For a practical scenario (for example), A user with an area of 50m2 and a required energy output of 10 kW would be presented with the most suitable structural options, ranging from a two-column to a four-column system. The DSS would recommend System C as the optimal choice due to its ability to meet energy demands while minimizing long-term costs.

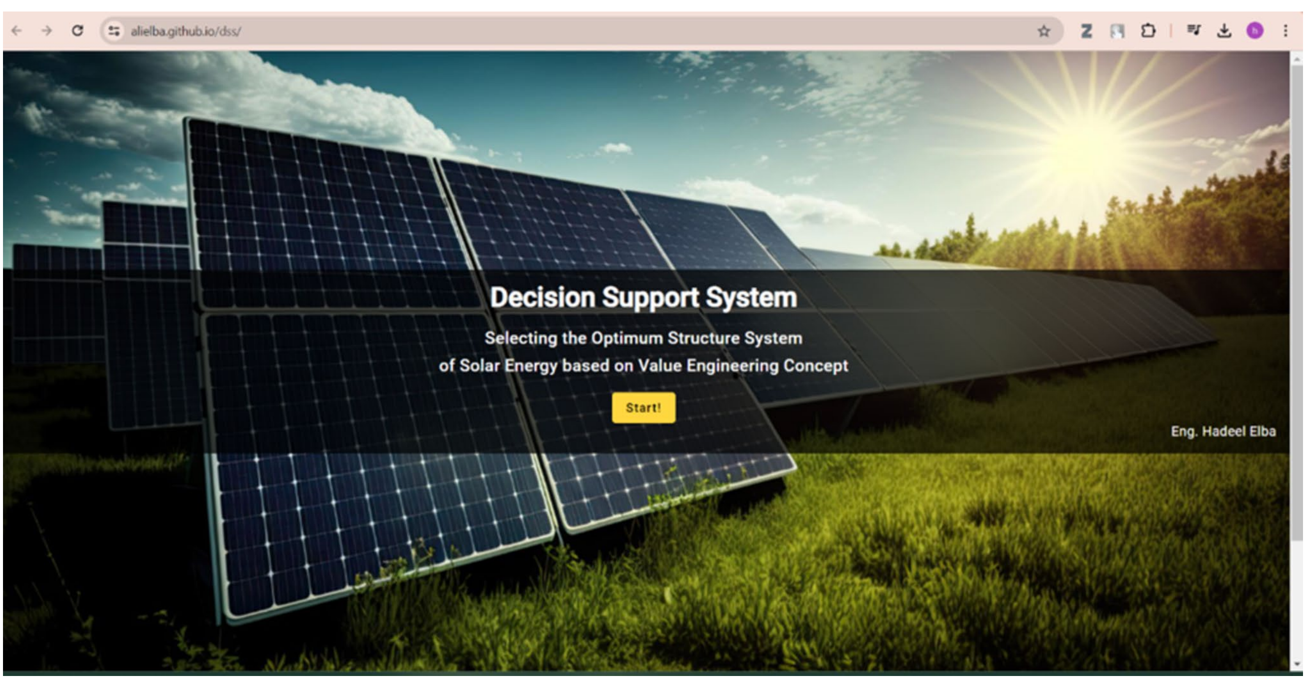


Fig. 10 DSS web application home page

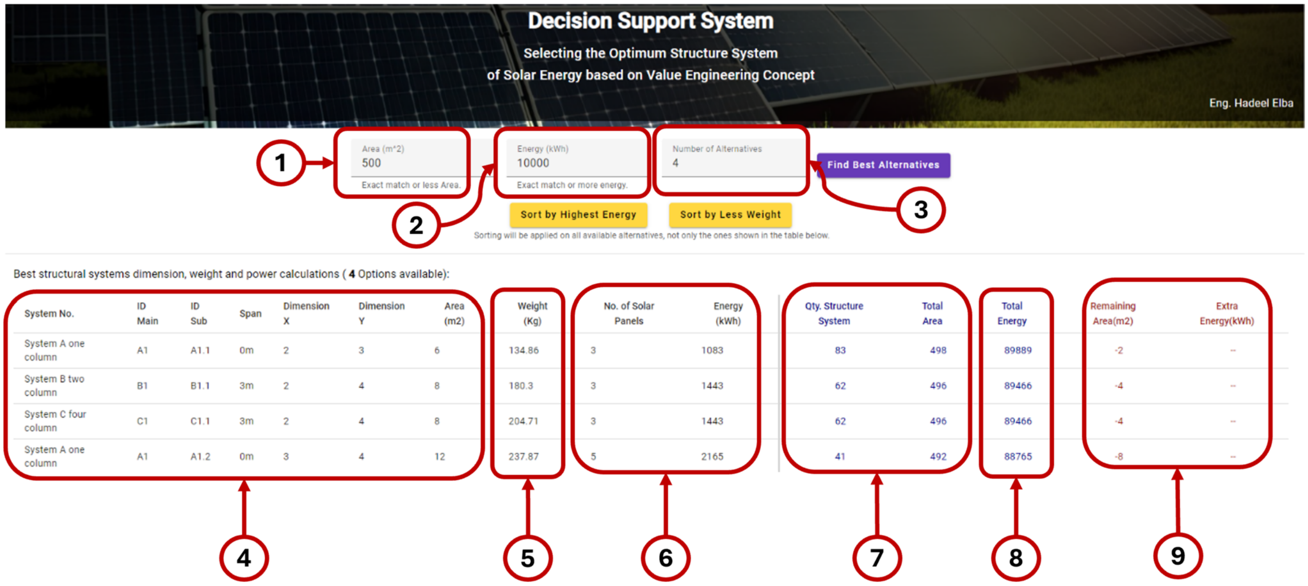


Fig. 11 DSS web application (Input & Output)

Example Scenario of DSS Interaction:

Let's consider a scenario where an engineer is tasked with designing a solar panel installation for a commercial rooftop. The engineer knows that the available roof area is 100m2, and the energy requirement for the building is 12 kW.

- Inputting Data into the DSS: The engineer enters the following parameters into the DSS:
  Available Area: 100 m^2.
  Required Energy Output: 12 kW (12,000 W).
- Receiving Optimized Solutions: Based on the entered data, the DSS processes this information and evaluates several possible structural configurations (e.g., one-column, two-column, or four-column systems). It uses pre-trained ANN models and FEM data to predict the energy output, structural weight, and area utilization for each system.
- DSS Output: The DSS gives the engineer a ranked list of optimized configurations.
  Option 1: Four-Column System (System C), which maximizes energy output (13 kW) and utilizes 90% of the available area, with a total structural weight of 1100 kg.
  Option 2: Two-Column System (System B), which provides 11 kW of energy output, uses 85% of the available area, and weighs 750 kg.
  Option 3: One-Column System (System A), which produces 9 kW of energy, utilizes 80% of the area, and weighs 550 kg.
- Decision-Making: The engineer can compare the options and select the most appropriate system that balances energy output, structural weight, and area utilization based on the results. For example, if maximizing energy output is the priority, the engineer may select Option 1 (Four-Column System), while a weight-constrained project may lead to selecting Option 3 (One-Column System).

The current version of the DSS is designed to display only structural configurations that meet or exceed the user's specified energy output. This may limit its usefulness for projects where lower energy outputs are acceptable. In future versions, we aim to provide users with a broader range of options, including configurations that may produce slightly lower energy but offer other advantages, such as reduced weight or cost savings. The DSS currently focuses on limited input parameters (area, energy output, and structural configurations). In real-world projects, other factors such as wind loads, environmental conditions, and specific material costs may influence the optimal design. Future improvements to the DSS will involve incorporating these additional factors for more comprehensive optimization. In future versions, the DSS could integrate material costs to provide a more detailed cost-efficiency analysis, helping users make more informed financial decisions alongside structural and energy considerations.

Conclusion and future works

The research methodology outlined here provides a clear and structured approach to exploring the potential of AI and web-based interfaces in enhancing the design of steel structures for solar energy systems. The combination of data-driven AI models and interactive web interfaces holds the promise of revolutionizing the field of structural design for renewable energy infrastructure.

This study explores a flexible ANNs model that uses the capabilities of STAAD Pro V8i SS6 software and MathWorks® MATLAB® software for decision-making that can select an optimal structure system for solar energy systems on multiple criteria (such as area, various spans, fixed height, and solar panel fixed area) that may change independently and using weight optimization techniques. The optimization was performed using an ANN model to select the optimum steel structures for solar energy systems and forecast the total weight systems based on input parameters such as base area, span, and fixed height.

- This research has focused on two transmission line tower systems, self-supported suspension, and self-supported tension towers, which are prevalent worldwide.
- The study also suggests how to develop the FEM model that uses the capabilities of STAAD Pro software and Excel for analysis for optimization that enables decision-makers to use this database to select the optimal steel structure systems for solar Energy in keeping with the criteria established for that system.
- The model can choose an optimal solar energy system using a web-based interface. The web-based interface facilitates real-time design adjustments and user interaction, facilitating optimization. This study shows that FEM-ANN are very effective tools for determining the optimal bracing system and section for the steel structure. The absence of a commercial software package for determining optimal bracing systems is noted. A software program of this type can be developed further.

Moreover, a web-based interface adds a layer of user interaction, allowing real-time design adjustments based on specific project needs. This interface facilitates selecting the best solar energy system by enabling users to input and modify parameters, receive instant feedback, and explore various design alternatives. The combination of the FEM and ANN models in this web-based environment ensures that decision-makers can optimize designs dynamically and make informed choices based on real-time data.

A key observation from this research is the lack of commercial software for optimizing steel structure bracing systems in solar energy applications. The study demonstrates that the combination of FEM and ANN is a highly effective tool for determining the optimal bracing system and structural sections. The absence of readily available commercial software for this purpose suggests a gap in the market that could be addressed through further development of specialized tools. A software package that integrates these optimization capabilities would greatly benefit engineers and designers working in renewable energy infrastructure by streamlining the design process and improving outcomes.

This study highlights the practical applications of integrating AI-driven ANN models with FEM analysis to enhance the optimization of steel structures for solar energy systems. The proposed methodology optimizes design efficiency and promotes sustainability by minimizing material usage and optimizing energy production. Developing a web-based interface enhances real-time optimization and decision-making, providing that the design of solar energy systems is adaptable to evolving project requirements. The results highlight the necessity of creating specialized software to enhance bracing systems, indicating opportunities for innovation in renewable energy infrastructure.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s41062-024-01831-9.

Funding Not Applicable.

Data availability All data, models, and code generated or used during the study appear in the submitted article.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Not applicable, as the study does not involve human subjects.

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