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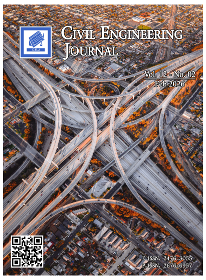

AI-Driven Shear Capacity Model of Steel Studs in Composite Structural Systems

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Abstract

In composite steel-concrete structures, shear connectors in the form of headed steel studs are commonly utilized to transfer longitudinal shear force developed at the interface between the two materials. To overcome the shortcomings of design codes, which frequently understate shear capacity and fail to take advantage of sophisticated computational methods, this paper presents an optimization attempt to estimate the shear strength of headed steel studs utilizing the Grey Wolf Optimizer (GWO) technique using MATLAB software. Data from 234 experimental tests are employed to identify and highlight key input parameters influencing the shear strength of headed steel studs. These key parameters include concrete compressive strength ($f'c$), diameter (D), and tensile strength of the steel stud shank (fu). After identifying and examining the limits of the experimental data, the proposed model has been developed using about 80% of the mixed raw dataset. The remaining 20% of the raw data is utilized to validate the proposed model. The predicted shear strength of headed steel studs closely matched the experimental results. This research offers an innovative strategy to measure the steel stud's shear capacity employing GWO, showing the current code's limitations. The GWO model showed excellent accuracy in predicting the shear strength with an R-value of 0.9922, indicating that the predicted value is in good agreement with experimental observations. Interestingly, the model's mean absolute error with 100 wolves in the GWO method was only 7.51%, showing the proposed model provides an improvement in shear capacity forecasting for practical structural engineering applications.

Keywords: Headed Steel Studs; Concrete-steel Composite Beams; Shear Capacity; GWO; Statistical Modelling Technique.

1. Introduction

It is well-known that utilizing concrete to withstand compression, while steel is utilized to resist tension in concrete-steel composite structures, is the most efficient strategy for studies on risk assessment to mitigate earthquake damage [1]. Compared to reinforced concrete (RC) structures, composite concrete-steel structures offer several advantages, including improved flexural stiffness, high strength-to-weight ratio, flexible construction, and ease of repair and retrofitting [2–4]. In these structures, shear connectors using angles, channels, and headed studs are essential to have suitable strength and ductility to adequately transfer stresses across the steel-concrete interface [5]. Among the different

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types of available shear connectors, headed steel studs are the most commonly used connectors in composite construction. Generally, the shear capacity and performance of the headed stud are affected by many factors, including concrete compressive strength, geometry and height of the stud, the tensile capacity of the stud material, welding capacity of the stud shank, reinforcement details and the direction of the casting of concrete [6]. Composite concrete-steel structures tests are generally used to estimate the shear strength of steel stud connectors [7, 8]. These tests are the source of the provisions recommended by most building codes to calculate the shear performance of stud connectors. In addition, the shear capacity of studs is governed by some problem aspects, specifically, the length of stud embedment in concrete, connection mode of failure, type of concrete material (i.e., normal or lightweight, fiber reinforced), and the type of composite element (such as concrete slab, concrete wall or beam, and push-out specimens, etc.) [6, 9, 10]. Also, it is noted that the key parameters used to estimate the shear strength, including concrete cylinder compressive strength (f_c'), headed stud steel tensile strength (f_u), and stud shank diameter (d), are not consistently available from a single source. These parameters have been widely used to develop and examine models utilized to predict the shear strength capacity of headed stud connectors [9].

Numerous experiments on composite concrete-steel systems subjected to different types of loading, including monotonic, repeated, fatigue, and biaxial loading, have been conducted to obtain the shear strength of headed steel studs. Researchers investigated the welded joint and headed stud steel to determine how mode II cracks grow with fatigue. The results indicated that the crack deflection in base material satisfied the electromechanical test systems criterion, whereas the crack deflection in weld metal did not [11]. An examination of advances in the field of predicting the strength and durability of composite beams that use bolted shear connectors was conducted. Review studies have also investigated the bolted connectors for reinforcing steel-concrete beams in the following domains: compared to headed stud connections, bolted shear connectors exhibit different load-slip behavior and fatigue performance [12, 13]. Moreover, the effects of different factors affecting studs' shear strength, such as concrete compressive strength, number and diameter of studs, and boundary conditions, have been investigated [14–22]. The common types of failure of headed steel studs in the concrete-steel composite construction, shown in Figure 1, are the failure of the stud shank, stud embedment, cracking of the slab, and concrete slab shear failure [23]. Other scholars proposed a four-type notched steel plate shear connector with heights of 50 and 75 mm and thicknesses of 9 and 12 mm, which were evaluated by push-out test. The authors observed that the failure of specimens started with concrete fractures, while the shear connectors fractured at the welding zone with the steel plate. The channel and angle shear connection parameters provided numerical values for shear capacity, which were compared to experimental results. Moreover, the shear capacity values derived from Eurocode 4 and the American Institute of Steel Construction standards revealed comparable outcomes [24, 25].

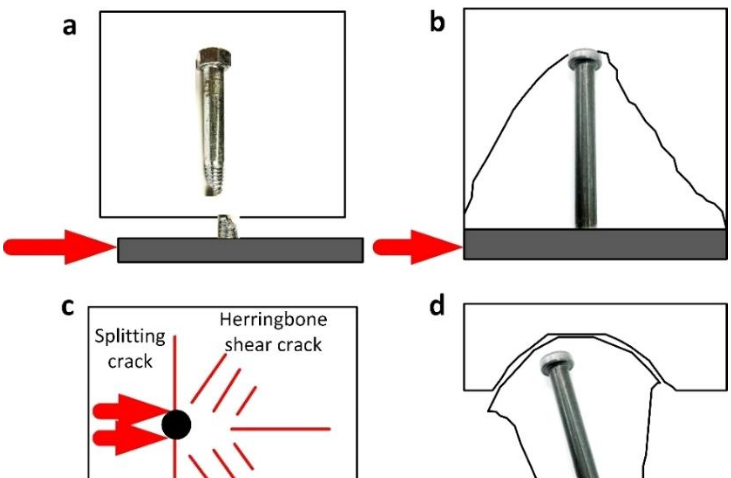


Figure 1. Modes of failure for headed stud connectors: a shank failure; b embedment failure; c slab cracking; d shear failure of slab (adapted and modified from Shim et al. [23])

Several studies have proposed non-AI approaches to determine the shear strength for steel stud connectors [26]. For example, Gyawali et al. [27] conducted push-out tests on headed shear connectors embedded in UHPC under both static and fatigue loading, showing that pre-fatigue cycles did not change failure modes and quantifying notable capacity gains (13.9–16.7%) due to optimized stud layout patterns. Xue et al. [21] investigated the shear behavior and design of headed studs embedded in steel–UHPC composite structures, contributing detailed experimental observations of connector performance under static loading. Zhu et al. [28] developed ensemble learning models to accurately predict stud shear capacity in UHPC, achieving excellent performance (best models reaching MAE= 11.2 kN, $R^2 = 0.988$) and providing

SHAP-based insight into feature importance. They also presented advanced finite element modeling of push-out tests using stainless steel studs, offering high-fidelity simulation data to support parameter sensitivity analysis and model validation. Lam [29] suggested a design procedure to estimate the shear strength for steel stud connectors in hollow-core precast concrete slabs.

Nguyen & Kim [30] and Ellobody & Young [31] proposed a nonlinear finite element model to evaluate the behavior of steel stud connectors in composite construction due to push-out test loading. Shahabi et al. [32] investigated the shear strength of headed stud shear connectors when subjected to high temperatures. This is a critical area for fire safety design in composite structures. Understanding how these connectors behave under elevated temperatures is essential for ensuring structural integrity during fire events [33]. While this paper focuses on high-temperature behavior, it might not delve into the use of advanced optimization techniques or AI-driven models to predict this response. Using Grey GWO and AI could fill this gap by developing a predictive model for shear strength at high temperatures, offering a more efficient and accurate design tool than traditional experimental methods alone. Miraza [34] focuse on using FE modeling to determine the capacities of headed stud shear connectors in composite steel beams with concrete slabs. FE modeling is a powerful numerical tool for simulating complex structural behavior and can provide detailed insights into stress distribution and failure mechanisms that are difficult to obtain experimentally. This suggests a focus on numerical analysis and validation against experimental data. FE modeling is robust, and it can be computationally intensive and time-consuming. This paper, published in 2023, might not explore the integration of AI-driven optimization techniques (like GWO) to create simplified, yet accurate, predictive models that can complement or even reduce the need for extensive FE analyses. GWO-based model offers a more affordable and quicker alternative for predicting shear capacity compared to detailed FE modeling.

Duan et al. [35] involved an experimental investigation of headed studs, specifically within steel Ultra High-Performance Concrete (UHPC) composite sections. UHPC is an advanced material with superior mechanical properties, and its interaction with shear connectors is a cutting-edge area of study. The paper would likely present experimental results on the behavior and capacity of studs in this specific composite system. However, it focuses on experimental findings for UHPC. While valuable, it may not explore the development of predictive models using advanced computational intelligence techniques for this specific material. using AI (e.g. GWO) to predict shear capacity from experimental data, could be extended to UHPC composite sections, providing a robust, data-driven model that can predict the shear capacity of studs in novel composite materials like UHPC. Ahn & Lee [36] investigated the strength of shear studs when used with high-strength concrete. High-strength concrete has different properties compared to normal-strength concrete, which can affect the behavior and capacity of shear connectors. The study would likely involve experimental testing or analytical modeling to understand these interactions. This study relies on traditional experimental or analytical methods. It probably does not incorporate modern AI-driven optimization techniques to develop a predictive model for shear stud strength in high-strength concrete. GWO-based approach, which has demonstrated high accuracy in predicting shear strength, could be applied to high-strength concrete applications, offering a more efficient and precise method for design and analysis. Introducing an AI-driven optimization approach using the Grey Wolf Optimizer (GWO) to predict the shear capacity of headed steel studs, addresses several limitations of existing methods. These include the underestimation of shear strength by current design codes, the absence of optimization-based models in this context, and the need for more generalized and reliable models that can handle diverse datasets and material properties. By focusing on a data-driven approach with a large experimental dataset, this work provides a robust and accurate predictive tool that can complement or enhance traditional experimental and FE analysis methods, and be extended to new materials like UHPC or high-strength concrete.

On the other hand, several studies used hybrid experimental and AI-driven techniques to estimate the shear strength for steel stud connectors. Abambres & He [37] used collected data from the literature to estimate the shear strength of headed studs by using an artificial neural network (ANN) modeling. The study revealed that the ANN model yields stud shear strength sounder than ones based on code procedure and equations presented in different codes of practice like Eurocode [38], AASHTO-LRFD [39], and Chinese Code GB50017 [40]. They showed that codes of practice underestimate the shear strength of the steel stud when compared to those resulting from experimental work [37]. Zhou et al. [41] applied machine learning techniques to predict the shear capacity of headed studs in steel–UHPC composite systems, offering insights into performance trends (e.g., group effects, UHPC thickness, fiber content) and developing user friendly design tools. Abambres & He [37] used Artificial Neural Network (ANN) modeling to estimate the shear strength of headed studs from collected literature data. Their findings indicated that the ANN model provided sounder results for stud shear strength compared to code procedures and equations. Avci-Karatas [9] discusses the application of Machine Learning in the prediction of shear capacity of headed steel studs in steel-concrete composite structures. The main literature studies highlight a research gap where, despite some analytical models existing to predict shear capacity, none have offered a trustworthy methodology or reliable guidance specifically utilizing the Grey Wolf Optimizer (GWO) technology. Although other AI techniques like ANN have been used, optimization strategies like GWO have not been investigated in this setting. The current research directly addresses this by applying GWO to this problem.

In this paper, the experimental push-out test results for the shear capacity of headed studs in concrete-steel joints were compiled to develop an optimization analytical model using GWO procedure concepts to evaluate the shear capacity of headed steel studs. A review of the literature indicated that applying these concepts in civil and structural engineering is limited. To date, little guidance or procedure assists researchers in predicting headed steel studs' shear strength using AI (e.g. GWO) with a reliable degree of accurateness were found. Hence, experimental results representing 234 datasets have been adopted to develop and validate the proposed model. It is thought that the proposed analytical model would serve as a solid tool to predict the shear strength capacity of headed steel studs in composite construction and would have a significant contribution to structural engineering applications. The findings from the current investigation regarding composite constructions may have a direct impact on the current practice of stud shear connectors.

1.1. Research Gap

By incorporating a novel computational optimization strategy, increasing forecast accuracy, and providing a useful tool for engineering applications that outperforms current techniques, the research improves the subject. However, several research gaps can be addressed when compared to previous studies:

a) Limitations in Existing Models and Codes:

- When compared to experimental results, previous research, and current design codes tend to underestimate the shear strength of headed steel studs.
- While some previous studies have created analytical models to forecast stud sh
- Ear capacity, none have offered a trustworthy methodology or reliable guidance that makes use of the Grey Wolf Optimizer (GWO) technology.

b) Absence of Optimization-Based Models

- Although shear capacity has been predicted using artificial intelligence techniques like ANN, optimization strategies like GWO have not been investigated in this setting.
- The current work presents an optimization method for estimating shear capacity using GWO, which hasn't been thoroughly examined in other studies.

c) Data Gathering and Model Validation

- In contrast to earlier research, which frequently depended on smaller datasets, this work improves forecast generality and reliability by using a complete database for model building and validation by compiling 234 push-out test datasets from multiple sources.

d) Parametric Impact and Screening Analysis

- The relative effects of important parameters on shear strength were not thoroughly assessed in earlier studies. The stud diameter has the greatest impact on shear capacity, followed by tensile strength and concrete compressive strength, according to the DOE (Design of Experiments) analysis for the parametric and screening study done in this paper.

1.2. Research Importance

It is common practice to use concrete-steel composite construction utilizing shear connectors to achieve maximum capacities and benefit from adjoining materials in this system. The main role of the headed steel stud connectors is to adjoin the two materials in composite construction to act as one member of full depth by transferring the longitudinal shear force at the interface. The design shear strength of the headed stud can be achieved using various methods and codes worldwide. Various methodologies can be investigated to properly understand their effects and how headed steel stud shear capacity influences structural stability. Thus, this research aims to resolve the problem using the latest grey wolf optimizer (GWO) computational methods. Using this optimization technique, a novel prediction model may examine headed steel stud designs' shear capability more effectively and precisely. The ideal solution of the presented model, which meets these characteristics, might be applied to new situations and produce results that are suitable for industrial implementations. The model was created and confirmed using 234 experimental data results from the literature. The present research shows that the model will accurately forecast the capacity of headed steel studs in shear and affect civil engineering practice. The paper's findings are novel and will advance headed stud connector technology.

2. Methodology

Figure 2 shows the overallstep-by-step methodology of the present work. It provides a clearer process starting from collecting the experimental data, followed by the GWO stage for training, through optimizing to validating.

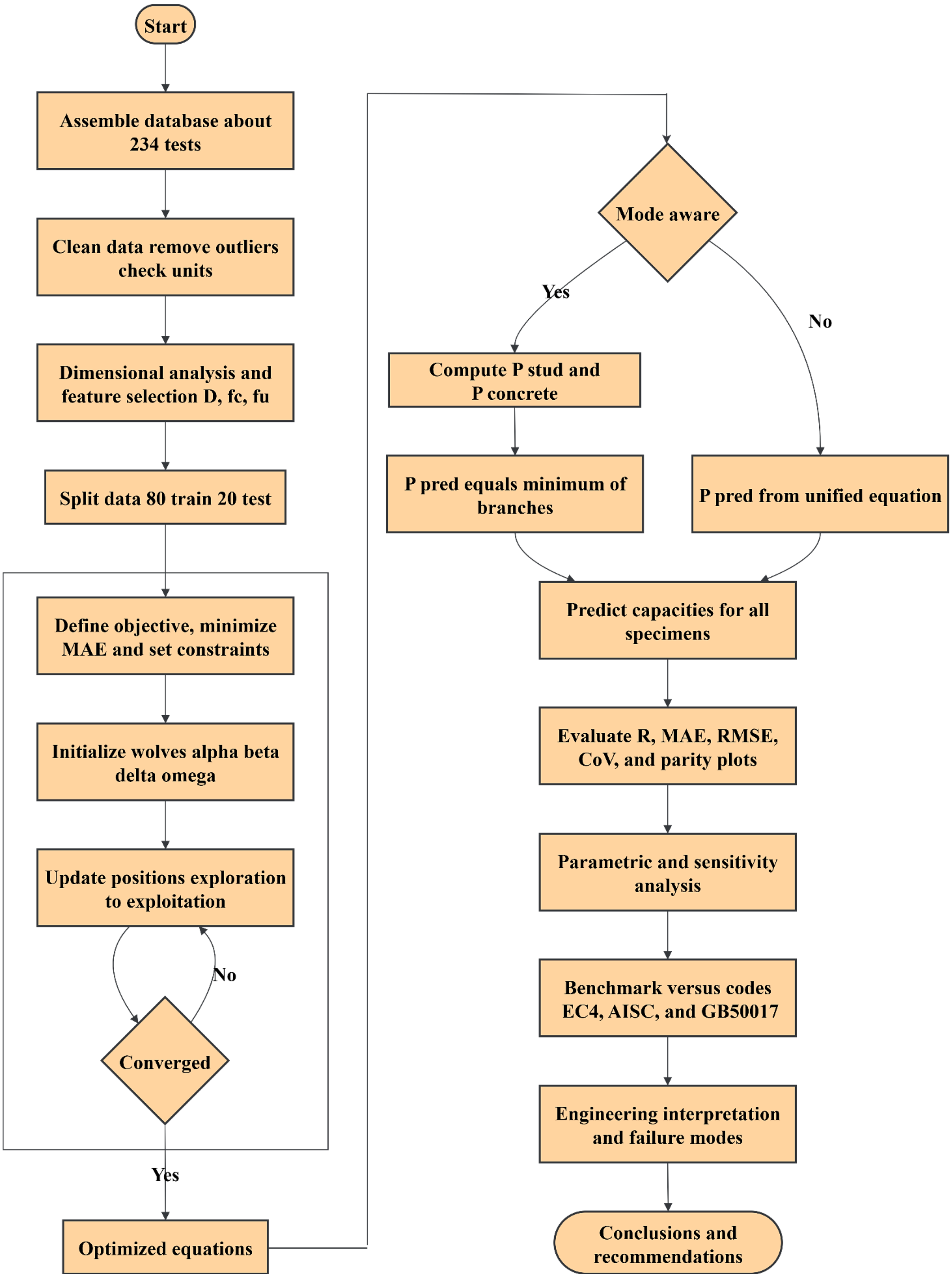


Figure 2. Methodology steps

2.1. Data Collection

It is previously indicated that many factors may influence the shear capacity of studs, including, but not limited to, the type of the composite structural element, geometrical and material aspects of the headed steel stud, and others related to concrete material aspects. In this research, data from previously published push-out experiments on the performance of headed stud connectors in composite concrete steel construction have been collected. Currently, about 234-point datasets have been assembled from various experimental work conducted by several researchers [20, 21, 23, 42]. These datasets have been compiled in Table 1. This table shows different aspects of collected data, such as geometrical parameters, material properties of input, and target/output variables. Experimental data presented in Table 1 revealed that the shear strength of the steel studs P_u , mainly affected by three factors including (i) diameter of the stud's shank, d, (ii) concrete compressive strength for cylinders at 28-day, f_c', and (iii) the stud material tensile strength, f_u. These parameters have been granted as the major input variables for models' development.

Table 1. Summary of collected experimental data on the shear strength of headed steel studs in the composite system

Data point	D (*mm*)	*fc* (*MPa*)	*fu* (*MPa*)	*Pu* (*kN*)	Data point	D (*mm*)	*fc* (*MPa*)	*fu* (*MPa*)	*Pu* (*kN*)
1	19.50	38.00	388.50	122.90	118	22.00	50.00	510.00	190.70
2	19.00	55.70	415.00	117.00	119	15.90	36.90	406.30	82.20
3	25.00	35.80	485.00	235.50	120	22.00	50.00	477.00	181.00
4	13.00	60.00	425.00	59.40	121	16.00	41.00	468.00	93.80
5	15.90	33.90	483.70	93.10	122	16.00	60.00	455.00	93.20
6	12.70	51.10	439.80	57.90	123	27.00	35.60	435.00	246.80
7	25.00	40.10	380.00	184.30	124	27.00	35.60	485.00	272.90
8	13.00	70.00	425.00	60.60	125	22.00	35.00	370.00	136.20
9	22.00	45.60	478.00	179.40	126	19.00	60.00	485.00	140.00
10	19.00	50.50	495.00	142.10	127	19.00	50.50	515.00	144.20
11	22.00	70.00	417.00	163.10	128	27.00	45.70	495.00	287.50
12	19.00	50.00	495.00	141.30	129	19.50	37.40	426.10	130.20
13	22.00	35.00	470.00	175.10	130	12.70	32.10	487.60	62.10
14	19.50	37.40	421.30	128.80	131	25.00	48.80	375.00	187.50
15	25.00	56.30	515.00	253.60	132	19.00	20.00	495.00	93.10
16	19.50	30.10	488.50	129.90	133	19.00	39.50	495.00	139.10
17	19.50	45.00	488.50	147.10	134	22.00	30.00	425.00	155.50
18	22.00	59.90	430.00	158.00	135	27.00	56.00	392.00	226.40
19	15.90	31.20	327.00	67.00	136	19.00	50.00	470.00	137.00
20	10.00	25.50	335.00	26.20	137	19.00	55.00	477.00	141.00
21	19.50	37.80	305.70	90.50	138	22.00	63.40	519.00	202.20
22	30.00	59.30	535.00	381.00	139	22.00	30.00	365.00	133.60
23	22.00	54.60	445.00	174.90	140	19.00	39.10	462.00	135.00
24	16.00	40.00	455.00	88.90	141	16.00	55.10	326.00	67.00
25	22.00	40.00	417.00	154.40	142	27.00	56.00	497.00	290.90
26	9.50	39.30	435.00	28.60	143	30.00	66.20	575.00	410.00
27	19.00	54.60	445.00	135.50	144	19.00	95.90	519.00	151.90
28	22.00	60.00	417.00	161.00	145	30.00	70.30	545.00	388.00
29	22.00	28.00	417.00	151.90	146	19.00	33.00	460.00	133.10
30	19.00	20.50	495.00	93.80	147	27.00	56.00	458.00	268.20
31	12.70	47.80	457.60	60.90	148	25.00	54.10	495.00	248.10
32	22.00	30.00	450.00	162.60	149	9.50	47.60	435.00	30.40
33	22.00	28.00	378.00	141.20	150	27.00	41.10	490.00	284.40
34	19.00	20.00	470.00	92.00	151	15.90	42.10	472.00	92.60
35	19.50	33.00	397.40	123.30	152	25.00	44.60	445.00	216.50
36	12.70	36.70	452.80	58.40	153	25.00	40.10	485.00	236.40
37	19.00	55.70	435.00	124.00	154	19.00	109.30	519.00	156.00
38	16.00	39.10	462.00	93.00	155	16.00	30.00	455.00	87.40
39	19.00	70.00	495.00	147.00	156	13.00	49.80	450.00	60.10
40	25.00	40.10	430.00	210.20	157	12.70	51.00	443.20	58.60
41	30.00	36.80	424.00	290.70	158	13.00	30.00	425.00	54.10
42	13.00	50.00	455.00	60.50	159	16.00	30.00	420.00	82.45
43	22.00	25.20	415.00	143.70	160	25.00	50.00	455.00	222.00
44	25.00	50.00	500.00	246.10	161	19.50	23.00	488.50	101.50
45	22.00	40.00	468.00	178.50	162	15.90	31.20	470.60	87.00
46	30.00	52.60	478.00	341.00	163	16.00	70.00	455.00	94.10
47	15.90	36.00	436.60	88.00	164	13.00	50.10	425.00	57.10
48	25.00	50.00	420.00	211.60	165	16.00	24.50	335.00	66.20
49	27.00	68.80	520.00	294.80	166	30.00	70.30	595.00	415.00
50	19.00	31.50	468.00	134.00	167	25.00	44.60	390.00	188.90
51	27.00	62.70	400.00	228.00	168	13.00	39.20	469.00	60.40
52	16.00	55.70	326.00	67.80	169	25.00	48.80	495.00	244.10
53	30.00	36.80	366.00	253.40	170	19.50	27.50	477.90	121.10
54	30.00	36.80	477.00	333.80	171	16.00	55.90	326.00	68.10
55	19.50	32.40	482.10	138.30	172	19.00	44.00	450.00	136.20
56	27.00	68.80	420.00	233.70	173	16.00	25.50	335.00	67.80

57	22.00	70.30	465.00	180.40	174	19.00	41.00	468.00	136.00
58	22.00	40.00	375.00	138.40	175	13.00	34.50	435.00	56.80
59	22.00	45.60	380.00	140.20	176	15.90	35.50	484.30	97.90
60	22.00	55.70	514.00	199.00	177	19.50	38.00	409.70	125.60
61	19.00	30.00	495.00	118.70	178	25.00	70.30	535.00	265.60
62	19.00	32.20	455.00	130.60	179	19.00	50.50	535.00	151.00
63	19.00	27.60	460.00	110.90	180	25.00	54.10	534.00	263.00
64	16.00	56.50	455.00	92.60	181	22.00	55.70	475.00	186.80
65	19.00	22.80	420.00	98.80	182	12.70	48.60	463.10	60.70
66	30.00	66.20	460.00	331.00	183	19.00	55.70	475.00	139.00
67	19.50	45.90	466.00	138.80	184	27.00	41.10	445.00	250.10
68	30.00	70.30	478.00	342.00	185	15.90	35.50	437.80	88.20
69	19.00	100.10	519.00	153.80	186	19.50	45.90	495.60	145.10
70	22.00	28.00	355.00	129.30	187	12.70	38.00	452.80	59.80
71	16.00	30.00	335.00	70.20	188	27.00	45.70	455.00	264.20
72	13.00	66.30	445.00	60.30	189	19.00	30.00	420.00	111.50
73	10.00	39.20	465.00	38.50	190	9.50	32.40	435.00	27.90
74	19.00	40.30	519.00	147.10	191	19.50	38.00	434.30	131.20
75	25.00	48.80	455.00	220.80	192	27.00	41.10	378.00	217.90
76	27.00	62.70	460.00	270.20	193	25.00	35.80	430.00	208.70
77	27.00	35.60	375.00	214.90	194	15.90	31.20	420.00	80.80
78	30.00	43.50	455.00	317.00	195	22.00	31.50	430.00	157.50
79	19.00	58.50	425.00	123.00	196	19.00	38.70	519.00	146.80
80	15.90	31.60	469.00	90.90	197	19.00	27.00	460.00	108.80
81	19.00	55.70	425.00	121.00	198	27.00	68.80	465.00	271.80
82	22.00	50.50	515.00	197.20	199	12.70	51.10	459.60	60.50
83	16.00	50.50	455.00	92.10	200	22.00	31.50	350.00	134.00
84	19.00	30.80	460.00	127.90	201	19.50	41.70	488.50	146.00
85	27.00	50.50	390.00	224.30	202	22.00	28.80	420.00	153.40
86	22.00	31.50	468.00	176.30	203	27.00	50.50	500.00	289.60
87	19.00	38.40	455.00	134.20	204	19.00	18.30	420.00	85.80
88	25.00	35.80	380.00	181.60	205	22.00	50.90	470.00	183.00
89	25.00	54.10	455.00	224.50	206	22.00	50.00	420.00	160.70
90	22.00	54.10	534.00	204.00	207	30.00	52.60	521.00	372.00
91	27.00	45.70	385.00	222.00	208	9.50	36.60	435.00	28.20
92	19.00	50.00	420.00	114.95	209	22.00	25.20	375.00	139.50
93	15.90	35.50	419.00	84.40	210	19.50	33.00	417.90	127.40
94	22.00	55.70	419.30	189.00	211	9.50	45.50	435.00	29.10
95	13.00	40.00	500.00	56.00	212	12.70	48.60	465.10	61.40
96	19.50	45.90	425.00	126.60	213	19.00	40.00	495.00	140.20
97	22.00	35.00	404.00	159.80	214	30.00	43.50	513.00	358.00
98	22.00	55.70	435.00	201.00	215	19.50	35.90	485.50	144.60
99	30.00	66.20	530.00	368.00	216	19.00	30.60	460.00	125.70
100	22.00	45.60	435.00	162.50	217	25.00	57.30	426.00	213.70
101	12.70	48.60	412.50	56.70	218	13.00	25.00	335.00	43.00
102	30.00	52.60	420.00	290.00	219	19.00	50.90	468.00	138.10
103	22.00	25.00	345.00	128.60	220	27.00	50.50	460.00	267.80
104	30.00	43.50	389.00	278.00	221	22.00	60.00	450.00	176.00
105	27.00	30.50	430.00	242.80	222	22.00	50.00	455.00	173.70
106	15.90	35.50	321.50	68.10	223	15.90	33.70	483.70	91.50
107	30.00	59.30	488.00	340.00	224	22.00	60.10	500.00	190.60
108	19.50	37.80	385.10	121.90	225	12.70	38.00	449.40	58.90
109	15.90	42.10	436.40	90.00	226	12.70	36.70	446.00	58.70
110	27.00	30.50	479.00	253.10	227	19.00	19.80	420.00	90.30
111	19.50	28.20	466.90	123.30	228	12.70	48.60	523.90	64.90
112	25.00	44.60	490.00	242.20	229	16.00	50.00	420.00	88.40
113	19.00	55.00	495.00	145.00	230	19.50	37.80	342.00	102.00
114	27.00	62.70	515.00	292.20	231	12.70	36.70	451.40	57.80
115	19.00	38.10	519.00	145.00	232	12.70	37.40	488.30	61.80
116	12.70	38.00	450.10	59.10	233	30.00	59.30	438.00	313.00
117	27.00	30.50	380.00	213.40	234	19.50	37.40	378.30	120.20

To facilitate the application of the developed analytical model by researchers and professional engineers in structural practice, it is intended to implement only three major variables, i.e., D, f_c' , and f_u, in the development of the proposed model used to determine the shear capacity of stud connectors. Keeping in mind that previous investigations revealed that other parameters affecting connectors' shear strength, such as the embedment length, pattern and spacing of studs, welding quality and size, and orientation of the interface between steel and concrete during casting, have minimal impact on the shear strength of the connectors. Incorporating more variables in the proposed model is not practical for many structures in practice, science each has its own characteristics. The present study aims to provide a sound and comprehensive study for researchers to obtain a simple and reliable model that ensures the convergence of amplitude scattering for the numerical solution of experimental results, which is considered a substitute for experimental testing. It is well known that models established using statistical approaches like Artificial Neural Network (ANN) and artificial intelligence techniques are usually sensitive to the size of datasets implemented in their development. Accordingly, the size of the dataset used for model development and validation is crucial since it highly impacts the correctness of the model results. Figure 3 shows the histograms of the dataset implemented in this work, while Table 2 presents the statistical aspects of the samples used in developing the suggested model.

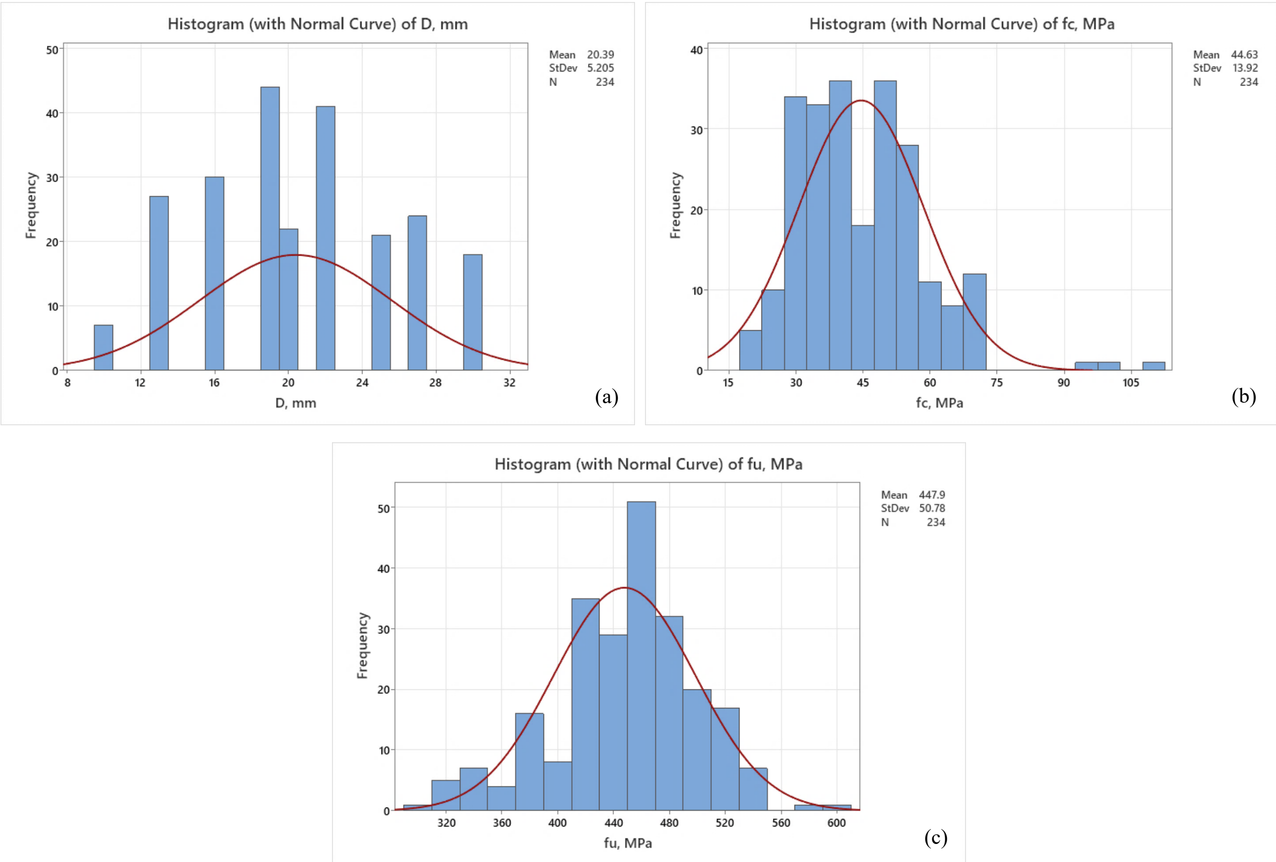


Figure 3. Histograms of independent input variables: (a) D, (b) *f'c*, and (c) *fu*

Table 2. Statistics for the developed model variables

Statistical variables	Parameters			
	Input			Response
	D (mm)	*fc (MPa)*	*fu (MPa)*	*Pu (kN)*
Mean (Average)	20.4	44.63	447.9	156.12
Standard Error	0.34	0.91	3.32	5.47
Standard Deviation (Std)	5.20	13.92	50.78	83.64
Sample Variance	27.1	193.69	2578.5	6995
Minimum Value	9.5	18.3	305.7	26.2
Maximum Value	30	109.3	595	415

3. Modelling Approaches

To create the best two-dimensional model for the shear capacity of headed steel studs, optimization is required, and its creation must take into account three crucial factors: (a) the formulation of the objective function; (b) the necessity for a precise approach to address the optimization issue; and (c) the definition of convergence criteria. The following subsections discuss these itemized points.

The proposed approaches to evaluate the shear capacity of headed steel studs take into consideration various considerations:

(1) As closely as feasible, the formulas should match the experimental results.

(2) The equations should be as user-friendly and straightforward as possible to use in any analysis.

(3) The proposed formula should agree with the relevant current design standards, allowing engineers to employ them with ease in the process of engineering design.

3.1. Fitness (Objective) Function

GWO's main purpose is to optimize the strength of the headed steel stud model in shear and find the best collection of unknown factors within the solution space. When applying the final form of the suggested model, the observed and forecasted values of the model for the shear capacity of headed steel studs were found to attain small differences. Suggested model convergence is obtained, and the search procedure is stopped once the coefficient that makes the objective function go down as little as possible is indicated. The intended model was simulated using MATLAB software to optimize the shear strength of the steel stud. As a result, there is not much of a discrepancy between the measured ultimate strength and that determined using the optimized equations' final form. The objective function of mean absolute error (MAE) is employed [43, 44]. The following expression can be used to find this objective function:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|NA - NP| \quad (1)$$

where, NP refers to the estimated value, NA is the observed value, and n is the specimen's size for the datasets.

3.2. Optimization Using Grey Wolf Optimized (GWO)

Figure 4 shows the hierarchical order of the grey wolf pack's social structure, illustrating the leadership and decision-making dynamics applied in the Grey Wolf Optimizer (GWO) algorithm. The grey wolf optimizer (GWO) draws inspiration based on the social system and the way those wolves hunt [45]. In the context of the GWO optimization technique used in this study, the wolf pack hierarchy shown in Figure 4 represents the roles of search agents in navigating the solution space. In the process of designing the GWO, the solutions that are deemed to be the fittest are considered to be the alpha (α) wolves, which act as the leaders. They guide the entire pack's movement toward the optimal region of the search space. This is achieved by imitating the social hierarchy that is found in grey wolves. The beta (β) and delta (δ) wolves, accordingly, represent the second and third-best ranking answers. They help refine the search direction by supporting the alpha and providing alternative search guidance.

Delta wolves follow the alpha and beta, representing third-best solutions that maintain the diversity of the search and prevent premature convergence. They also serve to test nearby solution spaces for improvements. The remaining candidate solutions have been given the designation of being omega (ω) wolves, which occupy the lowest rank, representing the least-fit solutions in the current population. They have a very rigid social dominant hierarchy, which is of particular relevance. They explore the outer areas of the solution space, which helps the optimizer escape local optima and improve global search capabilities. The exploration (hunt) technique is governed by α, β, and δ, who are accompanied by the ω wolves. By mirroring this natural hierarchy, the GWO algorithm balances exploitation (following alpha and beta) and exploration (movement by delta and omega), leading to efficient convergence toward the optimal parameters of the proposed shear capacity model in this study. The primary stages of grey wolf hunting, as per Muro et al. [46], are as follows:

- Following, chasing, and reaching the target (prey).
- Harassing, chasing, and circling the target till it comes to a stop.
- The assault on the target.

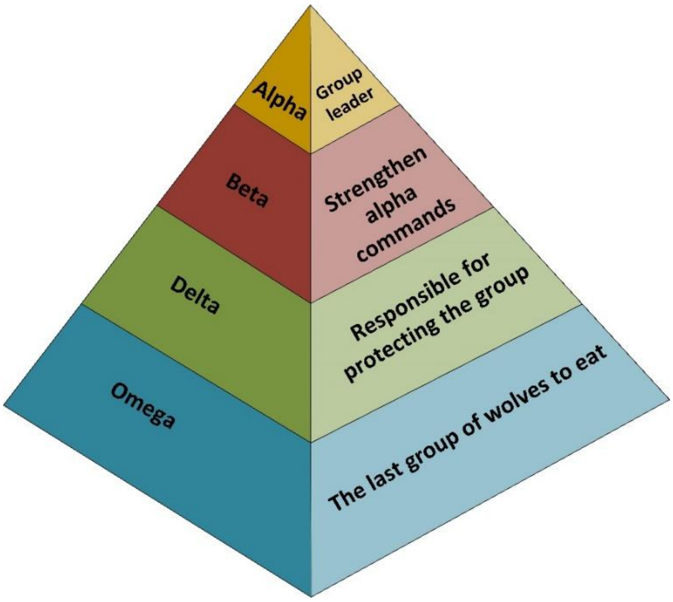


Figure 4. The order of the grey wolf pack's social structure

Figure 5 depicts these actions in detail as modeled in the GWO algorithm, which progresses through three stages. In the exploration stage, wolves (candidate solutions) chase, reach, and track the target by searching the global solution space for promising areas. In the transition stage, they harass, encircle, and pursue the prey, narrowing the search around the most promising solutions while maintaining diversity. Finally, in the exploitation stage, they fix the target and execute a coordinated attack, converging rapidly on the optimal solution. The social structure of grey wolves and their hunting approach is simulated in this work to create GWO and carry out optimization. When on the hunt, grey wolves frequently circle their target. This process ensures a balanced search strategy that combines global exploration with precise local refinement, enabling accurate calibration of the proposed shear capacity model. The subsequent are the formulas that model this encircling behavior.

$$D = \left| C \cdot X_p(t) - X(t) \right| \tag{2}$$

$$(t+1) = X\_p\ (t) - A \cdot D \tag{3}$$

where t stands for the recent epoch, X_p represents the prey's location vector, and X describes the location vector of a grey wolf. The coefficient vectors A and C are evaluated from the following formulas.

$$A = 2 \cdot a \cdot r_1 - a \tag{4}$$

$$C = 2 \cdot r_2 \tag{5}$$

where during the search process, the elements of a linearly reduced from 2 to 0, and the random vectors r_1 and r_2 are in the range [0, 1]. The GWO assumes that α, β, and δ wolves have a greater understanding of the location of the target because the place of the best (target) in an abstract search space is unknown. Figure 5 also depicts an illustration of potential positions for a grey wolf concerning prey. The potential solutions in the GWO need to use the equations below to update their locations following the locations of α, β, and δ.

$$\begin{aligned} D_\alpha &= \left| C_1 \cdot X_\alpha(t) - X(t) \right| \\ D_\beta &= \left| C_2 \cdot X_\beta(t) - X(t) \right| \\ D_\delta &= \left| C_3 \cdot X_\delta(t) - X(t) \right| \end{aligned} \tag{6}$$

$$\begin{aligned} X_1 &= X_\alpha(t) - A_1 \cdot D_\alpha \\ X_2 &= X_\beta(t) - A_2 \cdot D_\beta \\ X_3 &= X_\delta(t) - A_3 \cdot D_\delta \end{aligned} \tag{7}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{8}$$

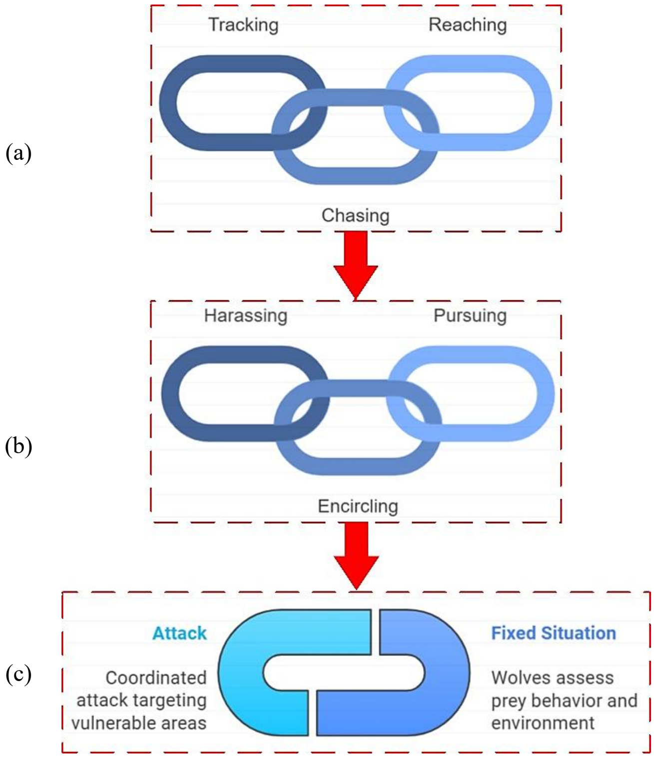


Figure 5. Flowchart of grey wolf hunting techniques illustrating (a) chasing, reaching, and tracking the target, (b) harassing, encircling, and pursuing (c) fixed situation and attack

Due to its straightforward parameters and straightforward mechanism, the GWO can be easily implemented and begins with an arbitrary group of grey wolves. In a 2D search space, a search agent updates its position per alpha, beta, and delta, as shown in the encircling position mechanism in Figures 6 and 7. Within the circle established by the locations of alpha, beta, and delta in the search space, the final location appears to be chosen at random, as can be observed. Alpha, beta, and delta thereby predict the target's position, while other wolves update their positions randomly around the target. In Figure ٦, the prey (optimal solution) is positioned at the center (X′,Y′), with wolves encircling it from multiple directions. This encirclement uses distance vectors (X′−X) and (Y′−Y) to progressively close in, ensuring convergence from diverse angles. Such symmetrical movement increases the probability of locating the global optimum rather than being trapped in local minima. Figure 7 expands on this by showing how position updates are influenced by the three leading wolves, alpha (α), beta (β), and delta (δ), each estimating the prey's location from different perspectives (C1, C2, C3) and distances (Dα, Dβ, Dδ). The remaining wolves (omega and others) adjust their movement based on these leaders' positions, converging towards the prey's estimated location (RRR). This cooperative guidance mechanism balances exploration and exploitation, which in this study ensures robust and mechanically interpretable predictions of steel stud shear capacity.

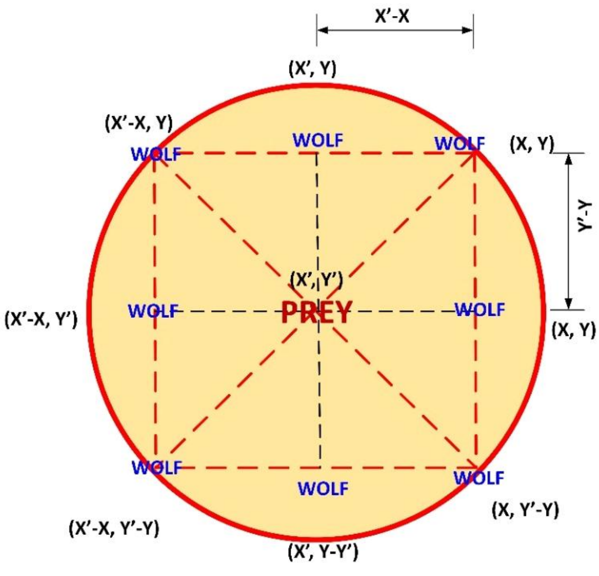


Figure 6. Updating the location around a pivot point

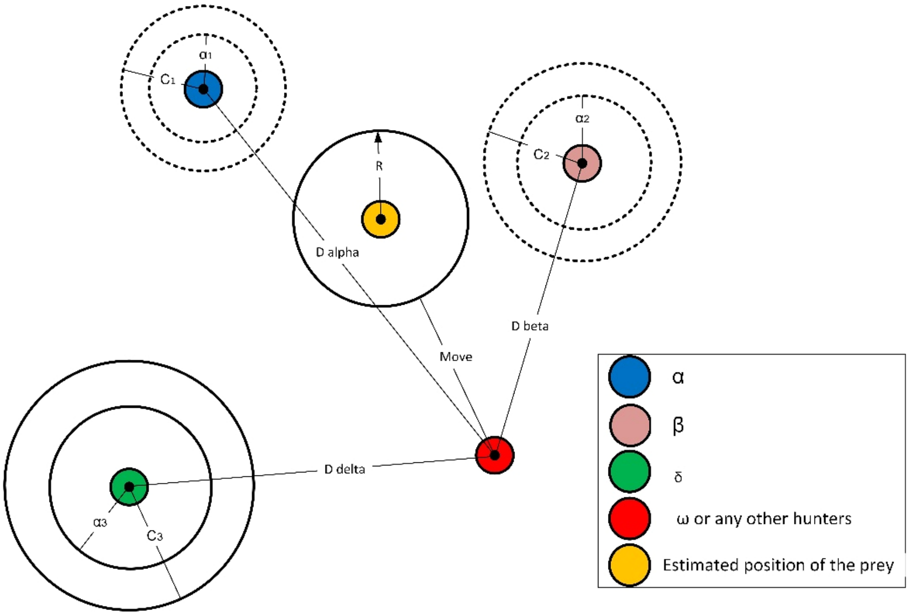


Figure 7. Position updating in GWO

Through using a numerical formula, as in Equation 8, that mathematically models the location updating of a grey wolf (X(t)) around a prey (Xp). A wolf can be relocated considering the distance between the wolf and the prey. If relocation around the prey is in a 2D space, it is a circle, in a 3D space, it is a sphere, whereas it is a hypersphere for location in N-D space using Equation 8.

3.3. Convergence Criteria

Due to the GWO exploration's iterative process, conditions can be used to stop the optimization process. The size of epochs of the GWO algorithm and the minimal amount of error essential to ascertain the ideal value of the objective function are the most well-known and frequently used two convergence considerations. The total number of iterations is determined by the level to which the optimization problem is complex, whereas the second criterion relies on the background experience of the overall perfect value. Mathematical problems may be utilized to evaluate or fine-tune an algorithm when the optimum value is known a priori. This, however, does not apply to real-world structural optimization issues where the optimum is unknown beforehand. Table 3 lists a number of the key GWO parameters.

Table 3. Main GWO parameters

Description	Details
Number of agents, N	The usual range is 10 to 40 agents. The range can be raised to 50–100 for some particularly difficult or unique issues.
Dimension of agents, D	It is evaluated by optimization issues.
Victors comprising the peak (upper) and lowest (lower) values of the n design variables.	The problem that needs to be optimized determines them. In general, different ranges can be applied for agents with different dimensions.

3.4. GOW Procedure to Evaluate Headed Studs Shear Strength

In this study, the dimensional analysis approach was used to create a good relationship between the output and the input parameters. If an equation's start point is known, then using equation inspection to non-dimensionalize this equation is useful. Nevertheless, in several common engineering practices, the equations are not known in other situations that are difficult to solve. Therefore, in such cases, the only method to solve is to perform experimentation.

The following points represent the main targets of performing non-dimensional analysis:

- To create the required scaled variables that assist researchers in experiment design and finally in reporting test outcomes.
- To get scaling laws to assure experimental performance from the proposed model performance.
- To evaluate patterns of the relationship between variables.

To achieve this purpose, many methods have been developed; however, the power series method is the most used. This method for obtaining scaled variables can be considered as a step-by-step procedure. By employing a compacting technique, the method of dimensional analysis can achieve decreased difficulty and a reduced number of test parameters.

Express each term in fundamentals $M(mass)$, $L(length)$, and $t\ (time)$

The relationship between the capacity of steel studs in shear (P_{GWO}) and the input variables ($D, f_y, and\ f_c$) may be written as a function:

$$P_{GWO} = f(\ D.f_{u.}\ f_c) \tag{9}$$

As any function can be expressed in the form of a power series, the form of the function may be considered as the sum of some terms of the series, taken as the products of the powers of the variables. When the function consists only of a single term, it can be regarded as the simplest form of the function:

$$P_{GWO} = F\ D^{n_1}\ f_u^{n2}\ \ f'^{n3}_c \tag{10}$$

Where, P_{GWO} is the shear capacity of steel studs, F is a constant D is the diameter of the stud. f_u is the stud steel material's ultimate strength, and f'_c is the concrete compressive strength, n_1, n_2 and n_3 are indices.

The dimensional consistency is achieved when the combined term on the right-hand side and left-hand side are the same, i.e., having the measurements of pressure. Expressing variables in Equation 10 using mass, length, and time terms.

$$D = l,\quad f_y = Ml^{-1}T^{-2},\quad f_c = Ml^{-1}T^{-2},\ \ P_{GWO} = MlT^{-2}$$

and

$$MlT^{-2} = F\ l^{n_1}\ (Ml^{-1}T^{-2})^{n_2}\ (Ml^{-1}T^{-2})^{n_3}$$

When the indices of each of mass (M), length (L), and time (T) variables have been equated to each other and the condition of dimensional uniformity has been met for these variables, then:

$$\begin{aligned} &M:\quad 1 = n_2 + n_3\ \rightarrow n_3 = 1 - n_2 \\ &l:\quad 1 = n_1 - n_2 - n_3 \end{aligned} \tag{11}$$

$$\begin{aligned} &n_1 = 1 + n_2 + n_3 \\ &\therefore\ n_1 = 2 \end{aligned} \tag{12}$$

$$\begin{aligned} &T:\quad -2 = -2n_2 - 2n_3 \\ &n_3 = 1 - n_2 \end{aligned} \tag{13}$$

Solving in terms of n_1, n_2, and n_3.

Thus, substituting into equation 10, the shear capacity of steel studs can be written as:

$$P_{GWO} = F\ D^{n_1}\ f_c^{n_2}\ \ f_u^{1-n_2} \tag{14}$$

Substitute and simplify:

$$P_{GWO} = F\ D^2\ f_u \left(\frac{f_c}{f_u}\right)^{n_2} \times 10^{-3} \tag{15}$$

Knowing that the terms $n_1, n_2, and\ n_3$ are random constants and when these terms are dimensionless, then this equation is satisfied. Evaluating the dimensions of each group shows that this is, in fact, the case. The constants $F$and n_2 can be found by using the GWO approach as presented in the previous subsections. The suggested model's flowchart is depicted in Figure 8.

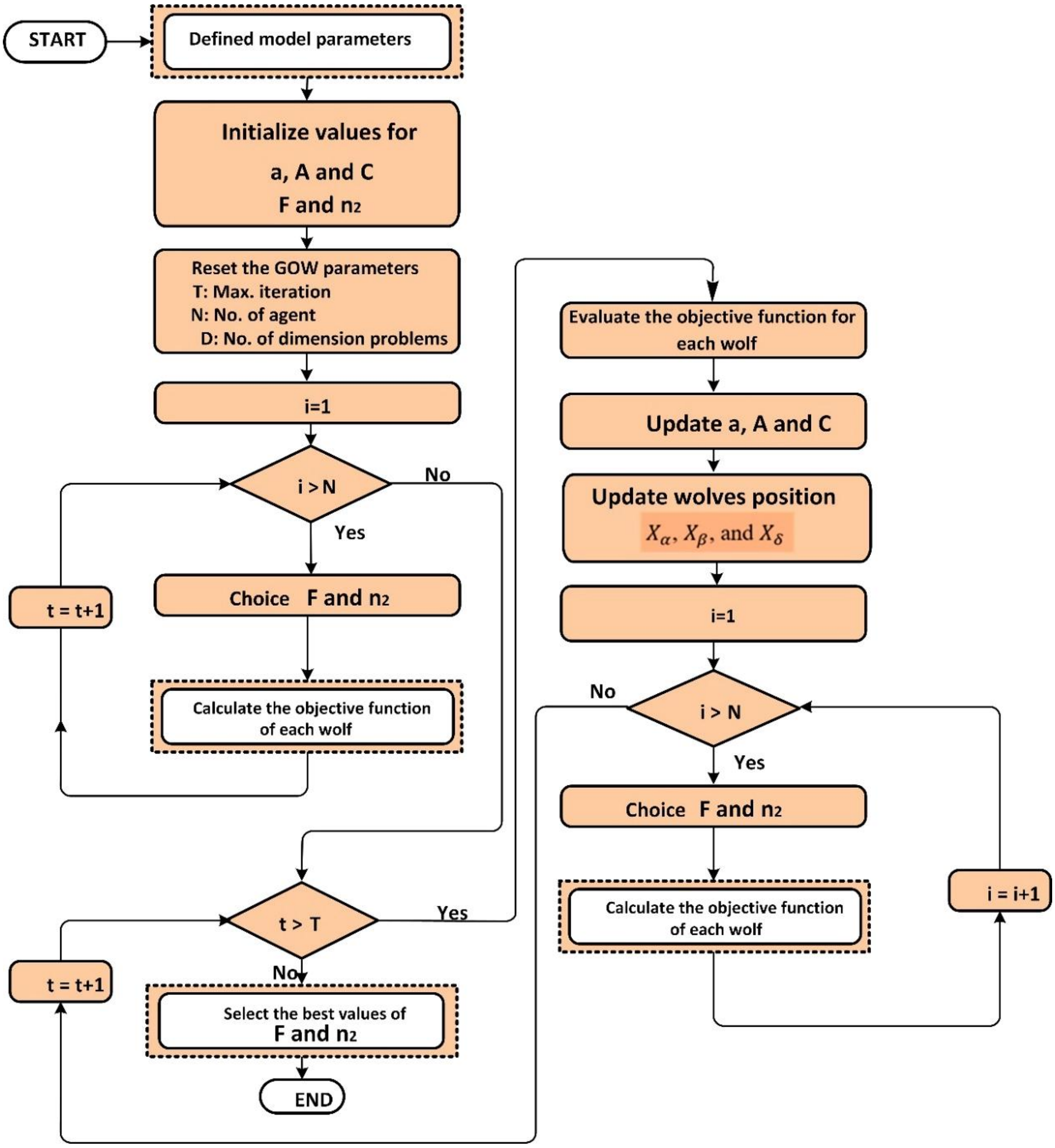


Figure 8. Proposed algorithm flowchart

4. Results and Discussion

4.1. Establishing the Proposed Model

The main objective of the present work is to develop a reasonable and trustworthy model per the GWO approach's capacity to evaluate the capacity of headed studs in shear. The ability to develop models within the data range used for their development employing computational intelligence techniques is well established. Therefore, the size of the dataset utilized during the simulation operation is a crucial issue because it has a considerable impact on the accuracy of the final model. A building dataset and a validation dataset used to validate the model after development were created from the entire database. 187 of the 234 investigated (as shown previously in Table 1) specimens (or 80%) were used to model construction, and the residual 47 samples (or 20%) were applied to evaluate the proposed model. To get over this restriction, Frank & Todeschini [47] claim that the optimal number of objects to specified variables for a model to be considered acceptable is 3. They argue that taking into account a number of 5 is better. In the current study, this proportion is considerably greater and equals 187/4, or about 46.75.

Figure 9 illustrates the convergence characteristic of the GWO algorithm in several wolves as pop size (40, 60, 80 and 100). The X-axis describes iterations and Y-axis shows the objective function value. The curves indicate the convergence speed and effectiveness of the algorithm to the optimal in every case. By establishing the objective function for 40, 60, 80, and 100 wolves, the GWO algorithm was applied. To enable the GWO algorithm to pick the wolves that could accomplish the lowest inaccuracy (error) and time duration, numerous wolf sizes are incorporated. The mean-absolute error (MAE) was applied as an objective function to choose an appropriate objective. In addition, the sizes of four wolves (40, 60, 80, and 100) were looked at. The GWO search algorithm continues until the specified convergence criterion is satisfied. Due to the changes in objective functions, the number of epochs in the current investigation was restricted to 5000. As shown in Figure 9, the search was steady after 4100 epochs. To ascertain which wolf size might minimize error and convergence time, a variety of wolves were investigated. This figure depicts that 100 wolves provide the optimal GWO algorithm solution since they accomplish the minimal objective function, as presented in Table 4. The optimal values for the coefficient factors demonstrated in the proposed model are listed in Table 4. Based on the observed findings, this table indicates that the suggested model's shear capacity of headed steel studs' prediction is reliable. The final form of the proposed model can be written as follows:

$$P_{GWO} = 1.544\, D^2\, f_u \left(\frac{f_c}{f_u}\right)^{0.319} \times 10^{-3} \tag{16}$$

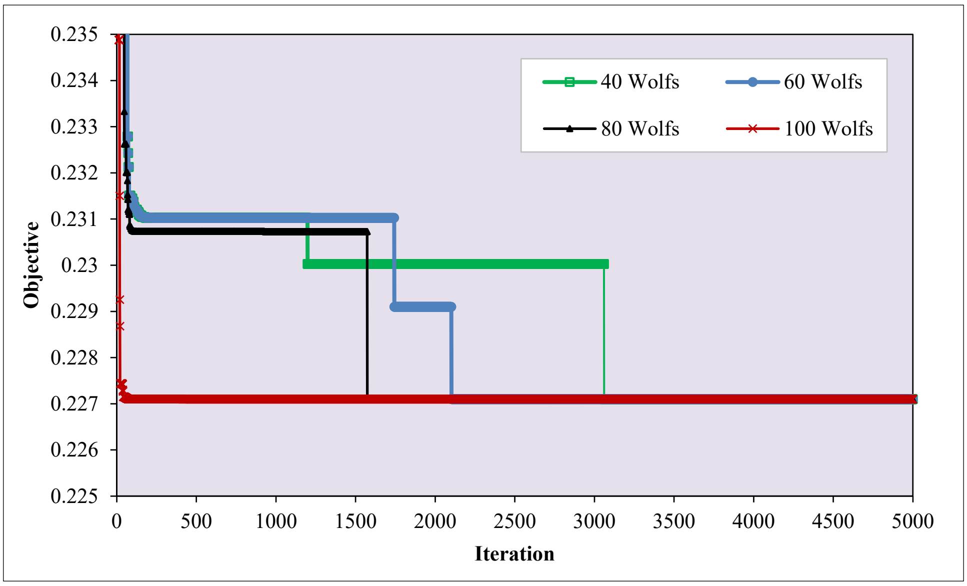


Figure 9. Convergence procedure for various wolf sizes

Table 4. Population size comparison

Population size	Description
40 Wolves (Green curve)	• The convergence is relatively slower compared to larger populations. • The objective value decreases gradually, stabilizing only after approximately 3000 iterations. • This indicates limited exploration capability with fewer wolves, leading to slower convergence.
60 Wolves (Blue curve)	• Shows a better balance between exploration and exploitation. • The convergence is faster than 40 wolves, stabilizing around 2000 iterations. • The objective value reaches a lower point compared to the green curve, suggesting a better solution.
80 Wolves (Black curve)	• Demonstrates more efficient convergence than both 40 and 60 wolves. • The algorithm stabilizes after about 1500 iterations, with a slightly better objective function value. • This highlights that increasing wolf numbers improves global search ability, though the improvement is incremental.
100 Wolves (Red curve)	• Provides the best performance among all tested sizes. • The algorithm converges almost immediately within the first 100 iterations, reaching the lowest and most stable objective value (~0.227). • The larger population significantly enhances exploration capability, enabling rapid convergence to the optimal solution.

The contribution of stud shear strength in Equation 16 is represented by ($D^2\, f_u$), where shear resistance is directly proportional to the cross-sectional area of the stud, as indicated by the quantity (D^2). The stud material (f_u) shear strength, which is consistent with basic shear stress principles:

$$P_{shear} \propto \tau_{max}\, A_{stud} \approx D^2\, f_u \tag{17}$$

Stud shear failure, which occurs when the applied force is greater than the material strength of the stud, is captured in this section of Equation 17. Concerning the concrete factor ($\left(\frac{f_c}{f_u}\right)^{0.319}$), the ratio of ($\frac{f_c}{f_u}$) represents the relative impact factor of concrete crushing and stud tensile strength. Higher concrete strength marginally increases shear capacity but does not entirely control failure, according to the exponent 0.319, which indicates a nonlinear dependence on concrete strength. Because stronger concrete may more evenly distribute shear loads around the stud, this exponent takes concrete crushing resistance into account. To account for units and empirical connections between material attributes, the constant (1.544×10^{-3}) is used as a calibration factor.

This formula (Equation 16) offers a unified shear strength model that takes into account both concrete crushing failure and stud shear failure. Since stud diameter (D) and material strength (f_u) are the two main determinants, stud characteristics largely govern failure. Rather than determining the primary failure mode, concrete strength (f'_c) has a secondary effect that modifies shear resistance. Because it strikes a balance between data-driven optimization and mechanical principles, Equation 16 is a semi-empirical failure model that engineers can practically use when designing composite structures.

The reasonable assumption of Pimentel-Gomes [46] states that when the CoV value of a model is less than 10%, it denotes high accuracy, while values of 10-20% state good accuracy, values between 20-30% reflect minimal sensitivity, and values over 30% are thought to reflect minimal accuracy. This criterion is displayed between the forecasted and observed values. For the designed suggested models, an adequate CoV-value of roughly 7.51% (100 wolves) was observed, which reflects better accuracy and measures the correctness of the target value. Additionally, the suggested model's close mean values (i.e., 1.07), which are depicted in Table 5, prove its correctness and durability.

Considering the relationship between the observed and estimated values in light of the following considerations, Smith [48] proposed restrictions to measure the precision of the mathematical model's efficiency by applying the correlation coefficient (R) in 1986:

- A strong relationship was identified if |R| > 0.8.
- A good relationship is identified if 0.2 | R | > 0.8.
- A weak relationship is identified if |R| is 0.2.

Table 5. The GWO algorithm's best estimates of the unknown coefficients' values

Parameters	F	n_2	M	SD	CoV %
100 Wolves	1.544	0.319	1.07	0.08	7.51

Figure 10 illustrates the comparison between the predicted shear capacity values obtained using the suggested model and the actual experimental results of headed steel studs. The data points are closely aligned along the diagonal line (1:1 line), which indicates a strong correlation between the predicted and measured capacities. Most points cluster tightly around this line, showing that the model provides reliable estimations with minimal deviation. Although a few scattered points at higher capacities suggest slight underestimation or overestimation in extreme cases, the overall trend confirms the model's accuracy and robustness in capturing the shear behavior of headed studs across a wide range of values. This validates the effectiveness of the proposed approach in practical applications. The predicted R value (0.9913) for the 100-wolf size of the suggested model. For the regression coefficient, the results indicate a good match between the observed and forecasted strength capacity values. This figure demonstrates that the suggested model produces the best outcome for the GWO because it has the minimum error

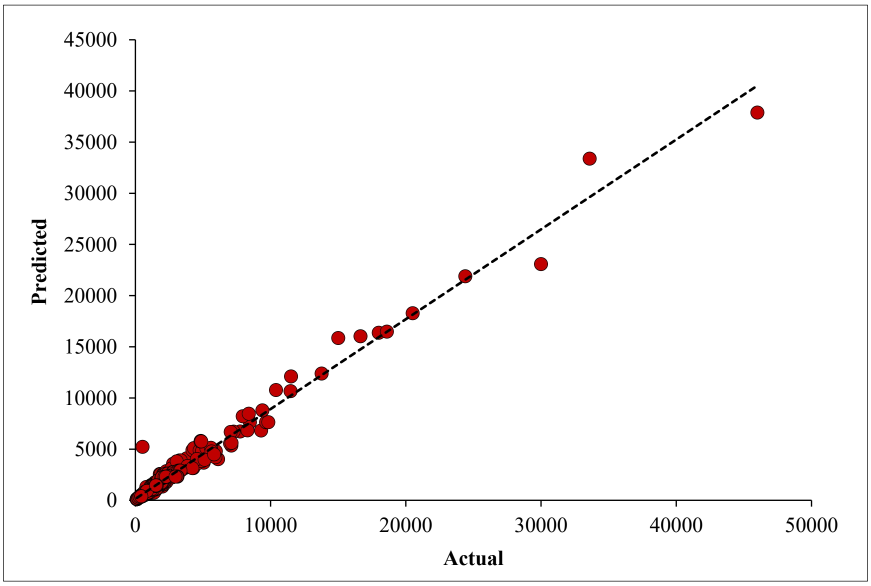


Figure 10. Comparison utilizing the suggested model between the estimated and the actual shear capacity of headed steel studs

4.2. Proposed Model Validation and Computational Efficiency

The scatter plot in Figure 11 compares the observed (actual) shear capacity of headed steel studs against the values predicted by the proposed model. The data points align closely along the dotted regression line, which represents perfect agreement between the predicted and actual capacities. This strong clustering along the diagonal suggests that the model demonstrates a high level of accuracy in estimating shear capacity, with only minor deviations at higher capacity values. The consistency of this alignment confirms the robustness and reliability of the proposed model, validating its applicability for practical prediction of headed stud performance under shear loading.

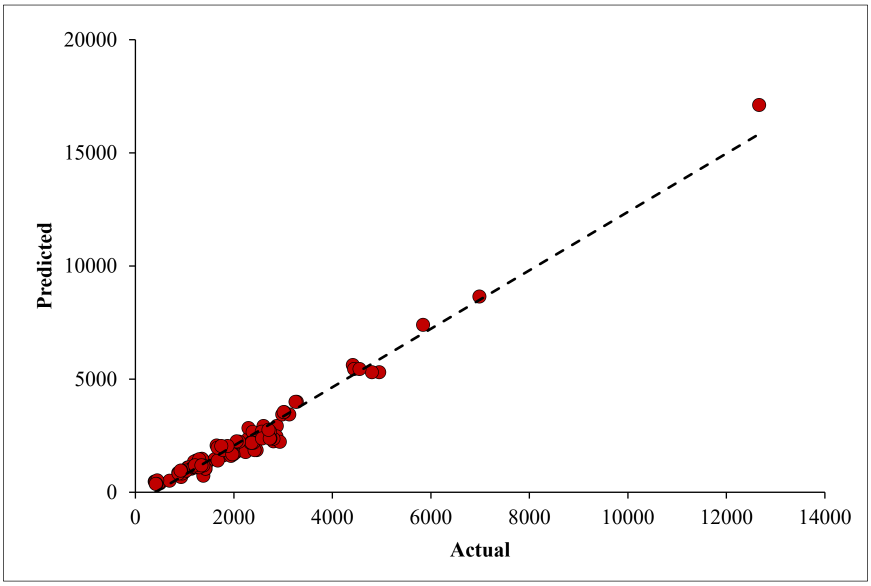


Figure 11. The comparison of the observed and expected values for the shear capacity of headed steel studs

The designed model's effectiveness was evaluated to validate the data. Forty-seven tested samples in total (20% of all datasets) were assessed. Their data were used for the model's verification procedure rather than for the optimization phase of the proposed model. The suggested model accurately and consistently estimated a mean value of 1.09, a standard deviation of 0.07, and a coefficient of variation (CoV) of 6.98%. Comparisons between the predicted results and the observed are displayed in Figure 11. These imply that the suggested model is reasonably reliable. A CoV value of 6.98%, as shown in the preceding subsection, denotes that the suggested model's anticipated results are extremely precise and consistent. The proposed model's mean value was extremely close to 1.0 (1.09), and the R-value, which is shown in Figure 11 (as 0.9922), demonstrates a strong connection between the observed and anticipated ultimate strengths. The proposed model was developed to forecast the shear capacity of headed steel studs accurately while considering various material qualities.

We appreciate the reviewer's insightful question. To address this, we conducted a comparative computational study using the same dataset and problem formulation, applying three optimization algorithms: Gray Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). All algorithms were executed under identical conditions with an Intel i7-12700H, 2.7 GHz processor and 16 GB RAM) for the same stopping criteria using MATLAB R2024a environment. The comparative results of average computational time per run are shown in Table 6. In addition to being the fastest among the tested algorithms, GWO demonstrated greater stability in convergence (lower variance of results across multiple runs), likely due to its balanced exploration–exploitation mechanism. These results confirm that the proposed GWO-based approach not only yields high predictive accuracy but also offers a computationally efficient solution compared with other widely used metaheuristic algorithms [49].

Table 6. Computational comparison

Algorithm	Population	Max iterations	Runs	Avg time per run (s)	Std. dev. (s)	Median iters to convergence	Notes
GWO	30	500	20	21.4	2.1	340	Fastest; stable convergence across runs
PSO	30	500	20	27.6	3.0	380	Slower than GWO under the same criteria
GA	30	500	20	33.2	4.2	410	Slowest; more variable run-to-run

4.3. Model Validity

Table 7 displays the appropriate model findings as well as the taken-into-account validation criteria. The statistical validation results confirm the robustness and reliability of the proposed GWO-based model. The correlation coefficient (R^2) reached 0.9922, which is well above the minimum threshold of 0.8, indicating a very strong linear relationship between the predicted and experimental shear capacities. The proposed model was externally verified on the testing datasets using the new requirements suggested by Golbraikh & Tropsha [50]. Regression lines (k or k') across the origin seem to require at least one slope to be closer to 1 [51]. The regression slopes (k = 1.03 and k′ = 0.89) also lie within the acceptable range of 0.85-1.15, confirming that the predictions are unbiased and closely aligned with the observed values. A confirmatory index of the additional reliability of models (R_m) was established in Roy & Roy [52]. The criterion is met if the index of reliability $R_m > 0.5$ (R_m=0.7), and hence, it provides additional assurance of the model's stability and generalization ability. The coefficient of correlation (R_o^2) ought to be near 1 between simulated and experimental values. Collectively, the constructed model meets the essential conditions. All suggested conditions are satisfied by the constructed GWO model.

Table 7. The suggested model's statistical specifications for extra verification

Equation	Condition	Suggested model	Equation
$R = \frac{\sum_{i=1}^{n}(PDA_i - \overline{PDA_i})(PDE_i - \overline{PDE_i})}{\sqrt{\sum_{i=1}^{n}(PDA_i - \overline{PDA_i})^2 \sum_{i=1}^{n}(PDE_i - \overline{PDE_i})^2}}$	$R > 0.8$	0.9922	(17)
$k = \frac{\sum_{i=1}^{n}(PDA_i \times PDE_i)}{PDA_i^{\ 2}}$	$0.85 < k < 1.15$	1.03	(18)
$k' = \frac{\sum_{i=1}^{n}(PDA_i \times PDE_i)}{PDE_i^{\ 2}}$	$0.85 < k' < 1.15$	0.89	(19)
$R_m = R^2 \times \left(1 - \sqrt{\lvert R^2 - R_o^2 \rvert}\right)$	$R_m > 0.5$	0.70	(20)
Where $R_o^2 = 1 - \frac{\sum_{i=1}^{n}(PDE_i - PDA_i^o)^2}{(PDE_i - \overline{PDE_i})^2}$, $PDA_i^o = k \times PDE_i$	-	-	(21)

4.4. Error Evaluation

The proposed model was developed, as previously mentioned, to forecast the shear capacity of headed steel studs. Bagheri et al. [53] suggested evaluating a distribution of the relative errors when comparing the model prediction abilities. Therefore, the following formula is used to calculate the absolute relative error (ARE) %:

$$ARE\% = \left| \frac{NA_i - NP_i}{NA_i} \right| \times 100 \tag{22}$$

Figure 12 provides insights into the error evaluation of the proposed model. The histogram reveals that the majority of the predictions fall within the lower error ranges, with 18 cases around 5% ARE and 17 cases around 10% ARE, indicating that most of the model's estimations are very close to the experimental values. As the error percentage increases, the frequency of occurrences decreases sharply, with only a few cases showing errors above 15%. Notably, only 2–3 cases exceed 20% ARE, which confirms that high-error instances are rare. The overlaid distribution curve demonstrates a right-skewed pattern, suggesting that the model tends to achieve small error rates more consistently, while larger deviations are exceptional. Overall, the figure validates the robustness and reliability of the proposed model, as the majority of predictions maintain an acceptable error margin, further supporting its practical applicability.

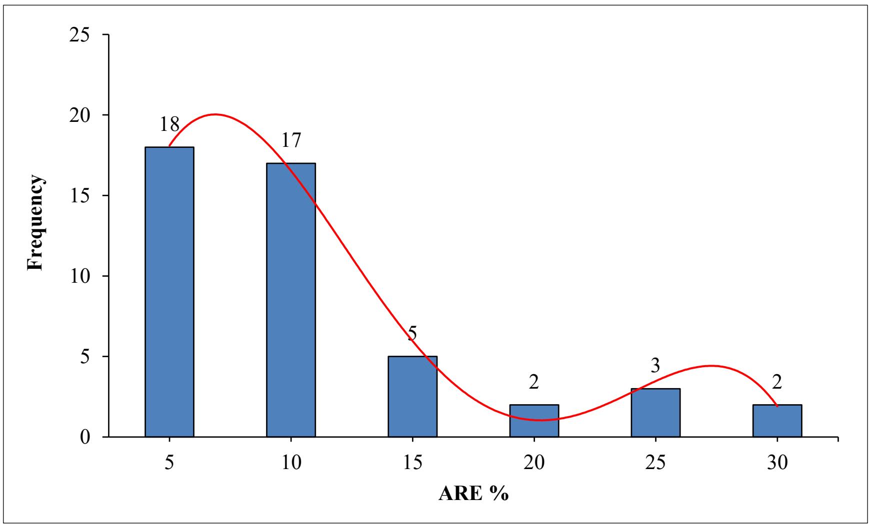
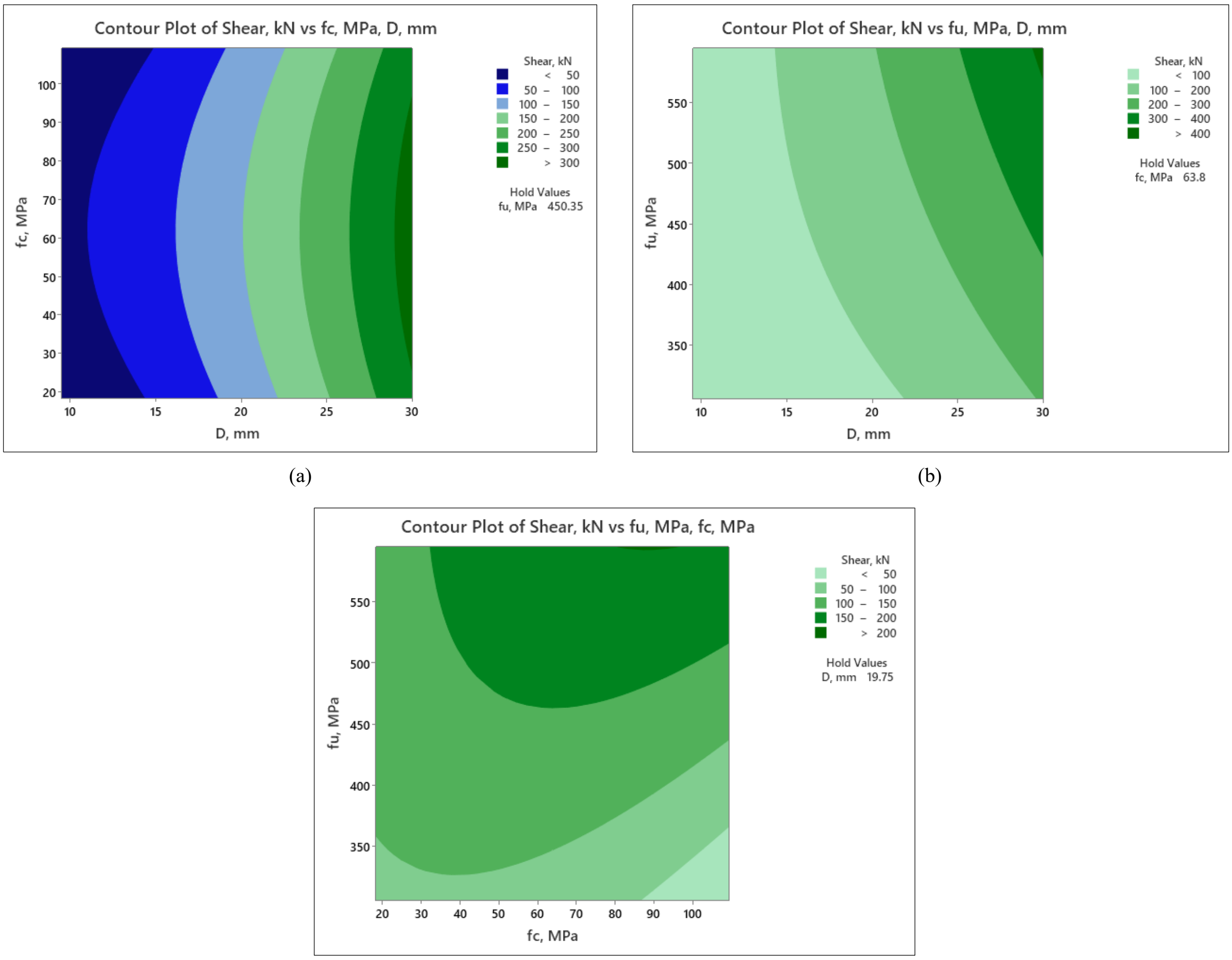


Figure 12. ARE distribution of the proposed model

4.5. Parametric and Screening Analysis

To estimate the influence of each parameter on the shear strength of headed studs, Figures 13-a to 13-c shows the capacity of headed studs in shear as a function of a pair of parameters. The analysis herein highlights which variables have the most significant contribution to the model's predictions and ensures that irrelevant or less impactful factors are screened out. It is noticed that the values of the shear strength of headed studs have been increased when increasing each variable value (D and f_c) and D with f_u up to a particular range, as shown in Figure 13. Furthermore, the shear capacity of headed studs has increased when increasing the f_c and f_u. Accordingly, the evaluation of the shear capacity of headed studs using tested parametric analyses can be achieved by selecting suitable parameters. This approach not only validates the robustness of the model but also enhances its interpretability by identifying the dominant parameters that govern the behavior of the system.



(a) (b)

(c)

Figure 13. Contour plots

For selecting the necessary input factors for the developed model, screening analysis is of great significance. It proposes a helpful method for assessing the contributions of every predictive coefficient to the required response. To achieve this goal, screening analysis is accomplished by providing the real response values against other parameters by using computer software. Screening analysis results for the key parameters involved in this study utilizing a standardized diagram shown in Figure 14. This figure shows the most important parameters influencing the values of the strength of headed studs in shear by order of the diameter of stud shank (D), the concrete compressive strength (f_c), and finally the ultimate tensile strength (f_u) for stud steel material. The Pareto chart shown in Figure 13 displays the results of the screening analysis for the developed model. In this figure, the main parameters influencing the shear capacity values of headed studs are shown in order, revealing that the stud diameter (D) has the most important influence on the headed studs' shear capacity followed by ultimate tensile strength of the steel stud, and concrete compressive strength, respectively. Accordingly, the parametric and screening analysis provides confidence that the model is both reliable and physically meaningful.

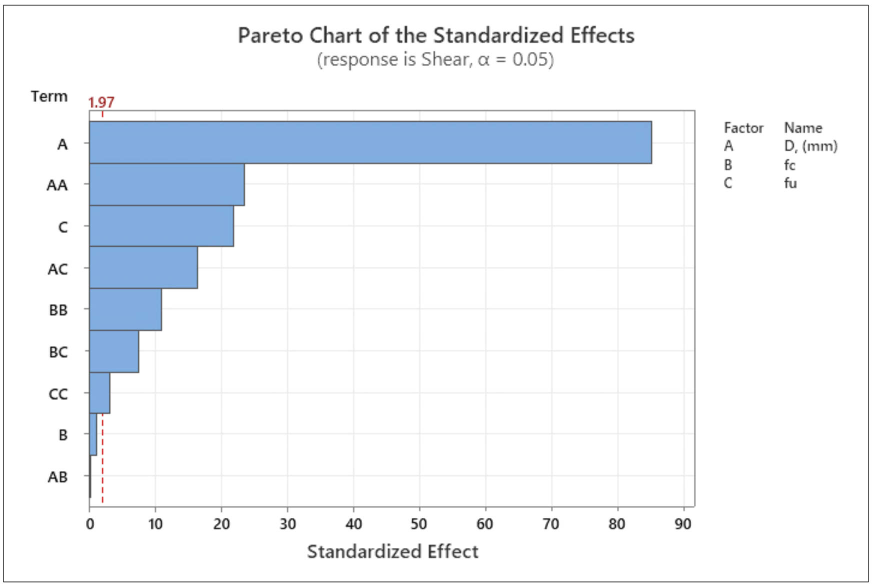


Figure 14. The findings of the screening analysis

4.6. Comparative Analysis

To contextualize the contribution of the present study, the performance of the proposed GWO-based shear capacity model was compared with previous predictive approaches available in the literature. Abambres & He [37] employed soft computing methods using artificial neural networks trained on experimental push-out tests and reported an average prediction error of approximately 8–12% with a correlation coefficient (R^2) of about 0.95. Similarly, Avcı-Karataş (2022) explored multiple machine learning algorithms, including extreme learning machines, and achieved R^2 values ranging from 0.94 to 0.97. More recently, Zhu et al. [28] developed ensemble learning models for shear prediction in studs embedded in UHPC and reported an MAE near 10 kN with R^2= 0.988. Compared to these approaches (Table 8), the proposed GWO model not only achieves superior accuracy (R = 0.9922 and MAE = 5%) but also explicitly incorporates failure mode considerations, thereby offering a more reliable and mechanically interpretable framework for engineering applications. This enhanced performance underscores both the methodological novelty and the practical value of the present contribution.

Table 8. Comparative performance

Reference	Dataset Scope	Approach	R^2	MAE	Notes
Abambres & He [37]	≈200 push-out tests	ANN-based soft computing	0.95	8–12%	Limited interpretability, black-box ANN
Avcı-Karataş [9]	Experimental dataset (studs)	Multiple ML (ELM, MPMR)	0.94–0.97	Not explicitly reported	Performance is strong but lacks mechanical meaning
Zhu et al. [28]	Studs in UHPC	Ensemble learning models	0.988	10 kN	Focused on UHPC, still black-box
Present Study (GWO-based Model)	≈234 push-out tests	AI optimization with failure mode consideration	9922	5%	Highest accuracy; failure modes explicitly modeled, mechanically interpretable

5. Conclusions

In this research, an analytical optimization model has been developed utilizing an optimized grey wolf optimizer (GWO) model to predict headed steel stud shear capacity and performance when utilized in composite construction. In this study, a 234-experimental dataset of push-out tests has been employed to develop the proposed model. Input key parameters adopted for statistical analysis included (i) shank diameter for the stud (D), (ii) concrete compressive strength (f'_c), and (iii) tensile strength of stud steel material (f_u). The main findings and key innovations include:

- The GWO method is an incredibly powerful approach that can be used to solve issues relating to structural engineering and can offer an optimum solution for the prediction of ultimate strength values utilizing a variety of parameters with high precision.
- The values for steel stud shear capacity predicted by the proposed model were in good agreement with the corresponding experimental results. The proposed model findings were comparable with the findings of the specimen tested.
- A robust and data-driven model that can be applied to different structural configurations was ensured by gathering a 234-point experimental dataset from diverse research.

- Using the developed model utilizing GWO's approach, a high correlation value of (R=0.9922). The ratio of predicted and experimental outcomes for the shear capacity revealed a maximum value of about 1.07. Hence, the evaluated statistical parameters indicated that the developed models are robust, reliable, and can be applicable for predicting the shear capacity of studs.
- The GWO ultimate strength model using a computational intelligence technique herein is the first innovation using data gathered from published experimental tests.
- The parametric and screening analysis results presented that the diameter (D) has the highest effect on the shear strength capacity of headed steel studs. The capacity is also impacted, albeit less so, by the concrete's compressive strength (f'_c) and the studs' tensile strength (f_u).
- Shear stud configurations can be optimized by directly applying the model in structural design software. Provides an affordable substitute for FEA and physical push-out testing. Increases structural safety by offering extra accurate predictions for failure modes.

To conclude, the proposed model is a valuable novel tool that presents a remarkable achievement for the existing engineering knowledge and practice to predict the shear capacity of headed steel studs used to design and analyze composite steel-concrete structures. This method can be expanded for future research to include novel composite materials, high-strength steel, and fiber-reinforced concrete. The framework can accommodate additional geometry ratios (e.g., stud height and embedment length) when consistently available, and outline how they would be incorporated (dimensionless scaling, cross-validated screening, and recalibration).

5.1. Limitations and Future Works

The GWO technique was employed in this study to develop the most accurate model possible for forecasting the shear capacity of headed steel studs. This model is according to datasets gathered from laboratory studies conducted previously. The types of parameters must be considered when collecting and analyzing such data because the number of parameters has a substantial effect on the structure of models. Moreover, the goal of this research is to develop a nonlinear model that achieves a higher level of precision in evaluating the target parameter. As a result, it is necessary to elaborate on the balance between the dataset input and its statistical features. This enables the analysis of a broader range of data and the development of models with enhanced capabilities. The final strategic goal of the current study is to design a new model with a greater degree of generality, for instance, by increasing the size of the dataset with a circular cross-section.

The current model is intentionally scoped and validated for headed studs under push-out testing; its inputs and dimensionless formulation (e.g., D, f'_c, f_u and $P/(D^2 f_u)$) reflect the mechanics of headed-stud action and the two dominant failure modes (stud-shear vs. concrete crushing). We therefore do not claim direct applicability to other connector typologies (e.g., channel-type, perfobond/notched plates, demountable/bolted connectors) without re-calibration. The current model should be treated as providing a nominal/characteristic resistance that is then converted to design resistance using the partial-factor (Eurocode) or resistance-factor (LRFD) formats used in practice.

6. Declarations

6.1. Author Contributions

Conceptualization, A.A.; methodology, A.H.; formal analysis, H.A. and M.H.; investigation, H.A. and M.H.; resources, M.H.; writing—original draft preparation, A.A.; writing—review and editing, R.A.; supervision, A.H.; funding acquisition, H.A. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

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6.5. Conflicts of Interest

The authors declare no conflict of interest.

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