Authors' Responses

Dear reviewer:

Thanks for reviewing the manuscript "Experimental Investigation of the Direct Shear Strength Parameters of Compacted Snow". The manuscript has been carefully revised and improved according to your comments. **In addition, beyond the original density range of 450 to 650 kg·m^{-3}, we have supplemented the experimental data by including tests with initial densities of 300 to 400 kg·m^{-3} under various sintering times and temperatures. The neural network framework was readjusted and recalculated based on the newly supplemented experimental data.** The questions you raised have been answered in detail; the author's response is marked in blue, and the changes made to the original manuscript are marked in red. The comments and corresponding Responses are as follows:

Summary

This paper presents an experimental setup to investigate the shear strength parameters of compacted snow. It also proposes a methodology for preparing compacted snow samples with distinct parameters, including initial density, sintering time, and sintering temperature. Using their apparatus, the authors obtained shear stress–displacement curves for samples under different normal loads. From these curves, they derived the shear strength based on the peak shear stress when present, or at a fixed displacement of 4 mm when no peak was observed. They also calculated the internal friction angle and cohesion using a Mohr–Coulomb relationship. Finally, the authors proposed a neural network to predict the shear parameters based on the four tested variables.

The paper is generally well written, and the methodology appears appropriate for the research question. While the novelty of the work is limited, the measurements and dataset produced in this study are valuable and warrant publication. My main concern is the choice of a neural network to predict a relatively simple relationship using only four variables. This choice seems driven more by popularity than by scientific necessity, especially since it is neither justified nor discussed. In addition, the discussion section would benefit from deeper analysis, as it currently reads like a list of bullet points. It may also be useful to add a dedicated section addressing the limitations and biases of the study, and how these may influence the results.

Major Comment:

Major Comment.1: The choice of the neural network needs to be explained and discussed. The choice seems to be rather “overkill” for such a simple relation (almost linear) with only 4 input variables. Usually, neural networks are chosen for non-linear behavior with a significant number of input variables. This chosen neural network is then prone to overfitting and migth boost the performance metrics. Also, neural network is better with a significant dataset, more around 200-300 data, rather than only 50. At least address it in the methodology and in the discussion should be necessary.

Response: Thank you for your comments. The authors provide point-by-point responses as follows:

(1) Rationality of using a neural network for analysis:

Although there are only four input variables, the interaction among them makes the strength trend more complex. As described in Section 3.2.2 of the original manuscript, with increasing sintering time, the shear strength of snow exhibits a nonlinear evolution: first a rapid increase, then a slow increase, and finally a decrease. This nonlinear behavior is further complicated by the combined effects of density, sintering temperature and other factors. The coupling between variables cannot be expressed by simple linear models. This also makes it difficult to determine snow strength parameters under different combinations of variables in engineering practice.

Traditional mathematical regression models (e.g., multiple linear regression or low-order polynomial regression) have greater limitations than neural networks. These methods require a predefined function form. They are sensitive to outliers. Their ability to handle multivariate interactions is limited. Polynomial regression can fit relatively complex curves, but the selection of high-order terms is subjective. It may also produce oscillations in data-sparse regions.

In contrast, a neural network has a strong function-approximation capability. It can automatically learn and represent the complex relationships between variables without requiring a specific function form. This is an advantage that traditional fitting methods do not have. Moreover, the neural network framework established in this study is highly expandable. In the future, as more data on factors such as loading rate, particle shape, and water content become available, these new data can be directly incorporated into the model. By adding input variables and retraining, a comprehensive computational model can gradually be developed to predict the shear strength of compacted snow under the influence of more factors.

Based on the above, the authors chose to use a neural network for data prediction and expansion.

(2) Selection of the dataset:

In the original manuscript, each condition in Table 1 represents a combination of variables, providing strength parameters (including shear strength values under four normal stresses). In machine learning, to enhance the generalization ability of the neural network, the shear strength values themselves were used as the dataset for network learning, rather than the strength parameters. In addition, the authors have supplemented experimental data for the density range of 300–400 $kg\cdot m^{-3}$ under various combinations of sintering time and temperature, and recalculated using the neural network. Currently, the neural network includes experimental data under 112 different normal stress conditions, totalling 448 data points. This fully meets the computational requirements for a four-variable neural network.

The authors have revised the relevant content in the manuscript, including the description of Table 1 and the dataset used for the neural network, to avoid any ambiguity.

(3) Issue of model overfitting:

We understand the reviewer's concern about the risk of overfitting in neural networks. The following explanation is provided from two aspects: network architecture and predictive performance.

Network architecture: After supplementing the experimental data, the authors also modified the dataset split. 70% of the data were used for training, 15% for validation (to monitor overfitting), and 15% for testing. This split ratio is a common practice in machine learning. It ensures that the training set is sufficiently large to learn the data patterns, while the test set is large enough to evaluate generalization ability. Table 1 shows the dataset splits and network architectures used by other researchers for BP neural networks. After revision, the dataset split of the neural network in this study matches those in other studies. Regarding the number of neurons, the authors again considered the risk of overfitting. The hidden layer was changed from two layers to one layer, with 10 neurons. This prevents the network architecture from being too complex and causing overfitting. For a regression task with only four input variables, the current model has a network structure that is as simple as possible, reducing the risk of overfitting from the architectural design.

Table 1 Data set partitions and network architectures for BP neural networks by other researchers.

Researchers	Data volume	Data split	Network architecture (input layer－hidden layers－output layer)
Hou (2024)	107	70% for the training set; 15% for the validation set; 15% for the test set	5-10-2
Feng (2024)	200	70% for the training set; 15% for the validation set; 15% for the test set	6-16-2
Liang (2024)	81	71 sets as the training set, 10 sets as the test set	3-5-3

Predictive performance: The performance difference between the training set and the test set is a key indicator of overfitting. A severely overfitted neural network typically shows very high accuracy on the training set but sharply lower accuracy on the test and validation sets. Also, during training, the training loss is low while the validation loss suddenly increases. Figure 1 shows the epoch-loss curve of the model. It indicates that as training proceeds, the validation loss decreases steadily and consistently. Furthermore, the comparison results in Table 3 of this study show that although the test set performance is slightly inferior to that of the training set, the decrease is limited, and the absolute accuracy on the test set remains high. This small difference is a normal generalization error, not a loss of predictive ability caused by overfitting.

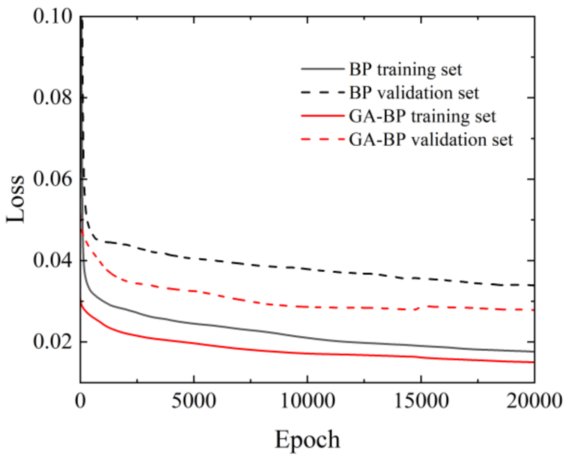

Figure 1: Epoch-loss curve

Table 3 Performance evaluation metrics for training and test sets.

	R^2	*RMSE*	*MAE*
Training set (*BP*)	0.986	9.65	7.15
Training set (*GA-BP*)	0.987	9.59	6.98
Improvement ratio (%)	0.1	0.62	2.4
Test set (*BP*)	0.958	14.76	10.83
Test set (*GA-BP*)	0.967	13.13	9.14

Improvement ratio (%)	0.94	11.04	15.6

From the above analysis, the neural network model in this study performs stably on both the validation set and the test set. The performance difference is within an acceptable range. Moreover, the model's behavior is consistent with the physical trends observed in the experiments (see Figs. 21–22 in the manuscript). Therefore, the authors believe that after revision, the current model has sufficient accuracy and generalization ability to support the conclusions of this paper. At the very least, there is no serious overfitting problem.

Corresponding content has been added to the original manuscript.

4 Prediction Using *GA-BP* Neural Network

As demonstrated in Section 3, the effects of various influencing factors on shear strength exhibit certain interactions and nonlinear relationships. Such behaviors are difficult to accurately capture using traditional function fitting methods. In contrast, neural networks possess more powerful capabilities in processing nonlinear data. To quantitatively characterize the specific influence trends of these factors, this section utilizes a genetic algorithm (*GA*) to optimize a back propagation (*BP*) neural network. Based on experimental data, a predictive model was developed with initial density, sintering time, sintering temperature, and normal stress as input variables, and shear strength as the output variable. The model aims to explore the underlying relationships among these parameters.

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4.1.1 Data Collection and Preprocessing

A total of 448 experimental data points were collected, with 70% randomly selected as the training set, 15% as the validation set, and the remaining 15% used for testing……

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4.2.2 Neural Network Prediction Results

After training the neural network model, 15% of the total dataset (67 samples), which were not part of the training set, were randomly selected as the test set. The accuracy of the trained neural network was then evaluated by comparing the predicted results with the actual values……

References:

Hou, L., Zhang, Q., and Du, Y.: Width estimation of hidden cracks in tunnel lining based on time-frequency analysis of GPR data and back propagation neural network optimized by genetic algorithm, Automat. Constr., 162, 105394, https://doi.org/10.1016/j.autcon.2024.105394, 2024.

Feng, Q., Xie, X., Wang, P., et al.: Prediction of durability of reinforced concrete based on hybrid-Bp neural network, Constr. Build. Mater., 425, 136091, https://doi.org/10.1016/j.conbuildmat.2024.136091, 2024.

Liang, J., Du, X., Fang, H., et al.: Intelligent prediction model of a polymer fracture grouting effect based on a genetic algorithm-optimized back propagation neural network, Tunn. Undergr. Space Technol., 148, 105781, https://doi.org/10.1016/j.tust.2024.105781, 2024.

Major Comment.2: Discussion: This section currently reads like a bullet-point list. It should be rewritten to improve the flow and strengthen the connections between paragraphs. There is also a need for an additional paragraph addressing the potential biases of the study. The paragraph on shear rate appears abruptly and feels underdeveloped, with only a few sentences. It should be better introduced and expanded, particularly regarding how shear rate affects the validity of the results, as this is closely related to Figure 4.

Response: The discussion section has been rewritten, with the section on shear rate from the original manuscript revised to improve the logical flow of the discussion:

4.3.1 Physical mechanisms governing the evolution of direct shear strength parameters

Initial density is the most important factor affecting the direct shear strength and strength parameters of compacted snow. An increase in density leads to more contact points between snow particles per unit volume and a denser internal structure (Butkovich, 1958; Mellor, 1977). This enhances interparticle bonding and frictional interlocking. As shown in Fig. 11, when the initial density increased from 300 to 650 $kg \cdot m^{-3}$, both cohesion and internal friction angle exhibited a significant increasing trend. Under the condition of sintering at –10 °C for 5 days, cohesion increased from 25.73 to 161.85 kPa, and the internal friction angle increased from 18.65 to 60.98°.

With increasing sintering time, the strength of compacted snow is jointly determined by sublimation and the formation of hydrogen bonds between snow particles (i.e., sintering). In the early stage of sintering, hydrogen bonds between snow particles form rapidly, while the density reduction caused by sublimation is not yet pronounced. During this stage, strength increases quickly. Afterwards, the sintering process stabilizes, and density continues to decrease. Under the combined effect of both processes, shear strength fluctuates slightly but remains relatively stable. As sintering time further increases, sublimation becomes the dominant factor, leading to a continuous decrease in strength.

During sintering, the protrusions on snow particle surfaces sublimate preferentially, making the particle shapes more regular. This reduces the surface roughness of snow particles, resulting in a continuous decrease in the internal friction angle. Cohesion follows a trend similar to that of strength: it first increases and then decreases gradually. As shown in Fig. 14, taking a density of 550 $kg \cdot m^{-3}$ and a temperature of –10 °C as an example, with sintering time increasing to 60 days, cohesion first increased from 53.54 to 141.85 kPa and then decreased to 131.99 kPa. Meanwhile, the internal friction angle decreased from 52.78 to 38.58°.

An increase in sintering temperature enhances the Brownian motion of water vapor, facilitating the formation of hydrogen bonds between snow particles (Abele, 1967, 1990; Colbeck, 1983a). A higher degree of sintering strengthens interparticle bonding and makes particle surfaces more regular. As can be seen from Fig. 16, when the sintering temperature increased from –25 to –5 °C, cohesion increased significantly (for the condition of density 550 kg·m^{-3} and sintering for 15 days, cohesion increased from 115.4 to 183.72 kPa), whereas the internal friction angle decreased from 48.69 to 41.74°.

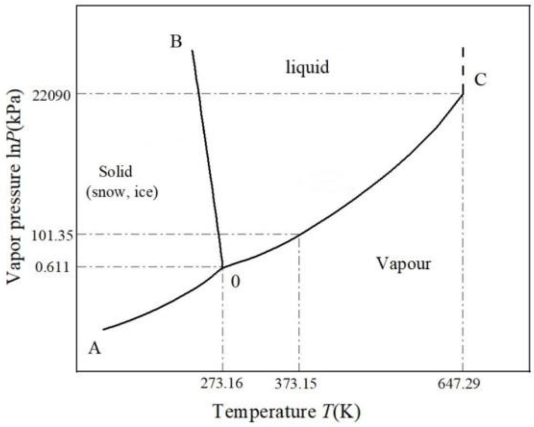


Figure 24: Phase diagram of water (A denotes the sublimation line, B denotes the melting line, and C denotes the evaporation line).

4.3.2 Comparison with existing studies

This study systematically investigated the variation trends of strength and strength parameters of compacted snow by considering initial density, sintering time, and sintering temperature. The effects of initial density and sintering temperature are consistent with previous findings (Butkovich, 1958; Ballard et al., 1965; Perla and Beck, 1982; Schweizer, 1998). Regarding the effect of sintering time, similar conclusions have been obtained from both field and laboratory studies (Jellinek, 1959; Zhuang, 2019; Fu, 2020; Yang, 2024). In contrast, Abele (1990) reported that the sintering strength of snow kept increasing without a decreasing trend. However, that study did not clearly describe the experimental details (e.g., ambient humidity and the sealing conditions of the specimens). Therefore, more refined experiments are needed in the future to further investigate the strength variation trends of compacted snow.

4.3.3 Highlights and limitations of this study

Through laboratory experiments and a neural network model, this study obtained baseline values of direct shear strength parameters for compacted snow under the following conditions: density 300 to 650 kg·m^{-3}, sintering temperature –5 to –25 °C, sintering time 0 to 60 days, and normal stress 25 to 100 kPa. Engineers can use these baseline values to perform deformation, bearing capacity, and stability calculations for snow facilities in polar cold regions. When snow type or environmental conditions change, new strength parameters can be obtained through laboratory tests. A quantitative relationship can then be established between the new indices and those from this study, allowing the baseline values to be corrected.

This study only considered initial density, sintering temperature, sintering time, and normal stress (25 to 100 kPa), with a loading rate of 0.8 mm·min^{-1}. How strength parameters of compacted snow change under other internal and external factors remains to be investigated in future work. Internal factors include snow type, water content, and particle size. External factors include ambient humidity, sealing conditions, loading rate, and normal stress.

References:

Abele, G. and Frankenstein, G. E.: Snow and ice properties as related to roads and runways in Antarctica, US Army CRREL Technical Report 190, Cold Regions Research and Engineering Laboratory, Hanover, ASIN B0007F4F4A, 1967.

Abele, G.: Snow roads and runways, CRREL Monograph 90-2, US Army Cold Regions Research and Engineering Laboratory, Hanover, 1990.

Butkovich, T. R.: Strength studies of high-density snows, Eos Trans. AGU, 39, 305–312, https://doi.org/10.1029/TR039i002p00305, 1958.

Colbeck, S. C.: Theory of metamorphism of dry snow, J. Geophys. Res. Oceans, 88, 5475–5482, https://doi.org/10.1029/JC088iC09p05475, 1983a.

Fu, X.: Test study on seasonal snow thermal properties and mechanical properties in Northeast China, M.S. Thesis, Northeast Agricultural University, https://doi.org/10.27010/d.cnki.gdbnu.2020.000222, 2020.

Jellinek, H.: Compressive strength properties of snow, J. Glaciol., 3, 345–354, https://doi.org/10.3189/S0022143000017019, 1959.

Mellor, M.: Engineering properties of snow, J. Glaciol., 19, 15–66, https://doi.org/10.3189/S002214300002921X, 1977.

Perla, R., Beck, T. M. H., and Cheng, T. T.: The shear strength index of alpine snow, Cold Reg. Sci. Technol., 6, 11–20, https://doi.org/10.1016/0165-232X(82)90040-4, 1982.

Schweizer, J.: Laboratory experiments on shear failure of snow, Ann. Glaciol., 26, 97–102, https://doi.org/10.3189/1998AoG26-1-97-102, 1998.

Yang, M.: Analysis on Mechanical Characteristics and Influencing Factors of Compacted Snow in Northeast China, Master's thesis, Northeast Agricultural University, https://doi.org/10.27010/d.cnki.gdbnu.2024.000351, 2024.

Zhuang, F.: Experimental Study on Snow Hardness and Its Testing Technology, M.S. Thesis, Dalian University of Technology, https://doi.org/10.26991/d.cnki.gdllu.2019.000727, 2019.

Specific comments (line number)

Comment.1:L63: Which studies? A few references are required here as it is the base of the novelty of the study.

Response: The author has added experiments on low-density snow within the density range of 300 to 400 kg·m^{-3}; therefore, the section regarding low-density snow in Line 63 of the original text has been omitted.

Comment.2:74–75: Is there any reference for this process?

Response: Regarding the principles of artificial snowmaking, relevant references have been added to the manuscript:

The test snow was artificially produced using machine-made snow through a process of atomization, cooling, and crystallization (Dong et al., 2023), closely mimicking the natural formation of snow. During snow sample-making progress, a high-pressure pump inside the snowmaking machine pressurized water to 6 MPa, which was then atomized into fine mist via a specially designed nozzle (Kang et al., 2018; Vijay et al., 2023). This mist was propelled by a high-speed fan, allowing it to travel a certain distance. Under subzero temperatures, the mist rapidly cooled upon contact with the air, forming ice nuclei that subsequently absorbed ambient water vapor to generate snow particles.

References:

Dong, P., Chen, Q., Liu, G., Zhang, B., Yan, G., and Wang, R.: Effects of Geometric Parameters on Flow and Atomization Characteristics of Swirl Nozzles for Artificial Snowmaking, *Int. J. Refrig.*, 154, 56–65, https://doi.org/10.1016/j.ijrefrig.2023.07.015, 2023.

Kang, Z., Wang, Z.-G., Li, Q., and Cheng, P.: Review on Pressure Swirl Injector in Liquid Rocket Engine, *Acta Astronaut.*, 145, 174–198, https://doi.org/10.1016/j.actaastro.2017.12.038, 2018.

Vijay, G.A., Moorthi, N.S.V., and Manivannan, A.: Internal and External Flow Characteristics of Swirl Atomizers: A Review, *At. Sprays*, 25, 153–188, https://doi.org/10.1615/AtomizSpr.2014010219, 2015.

Comment.3:L89: What is the resulting snow grain type, I'm guessing rounding grains or facets but was this observed? What exactly is meant by a natural sintering environment? Does this refer to isolating the sample from the surrounding air in the cold room? If possible, add a photo to Figure 1.

Response: Thank you for your comment. The authors provide a point-by-point response as follows:

(1) Regarding snow particle type:

After snow production, the authors observed the snow particles under magnification. The shape and size of the particles were recorded. The magnified snow particles are shown in Figure 1.

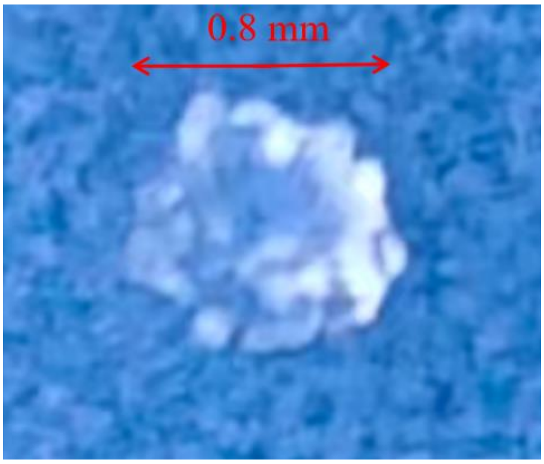


Figure 1: Morphology and size of experimental snow

Measurements indicated that the snow particle size ranged from 0.5 to 1.5 mm, and the particle shape was closer to a disc. Barrett et al. (2012) classified snow particle shapes based on supersaturation pressure and temperature during snow formation, as shown in Figure 2. Although the supersaturation pressure could not be measured during snow production in this study, the snow-making temperature (-5 °C) and the observed particle morphology were considered. Therefore, the snow type was classified as plates according to the classification of Barrett et al. (2012).

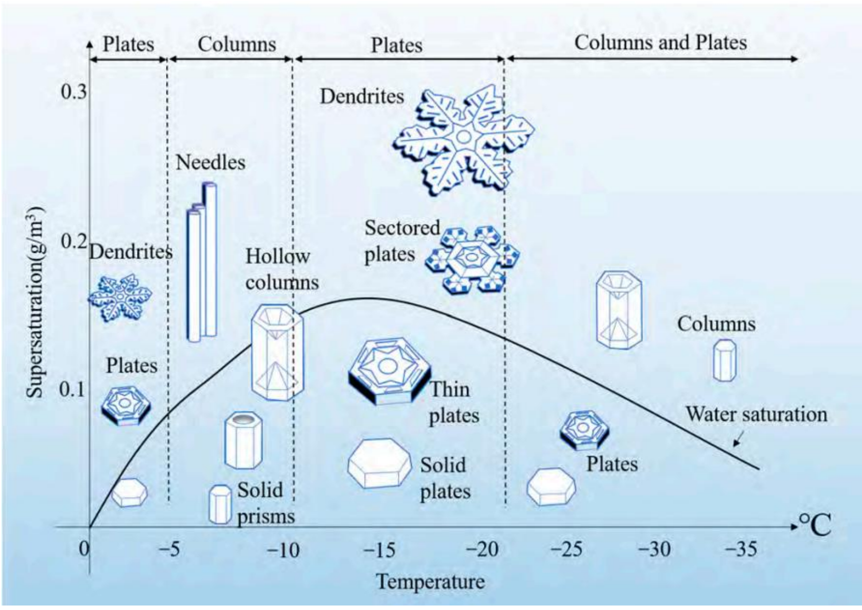


Figure 2: Classification of snow morphology (Barrett et al., 2012)

The relevant content has been revised:

Both types of snow exhibited similar physical properties. The natural snow had an initial density of approximately 200 kg·m^{-3}, while the machine-made snow had an initial density of approximately 300 kg·m^{-3}. According to Barrett et al. (2012), the snow crystals were classified as plate-like, with particle sizes ranging from approximately 0.5 to 1.5 mm.

References:

Barrett, J.W.; Garcke, H.; Nürnberg, R. Numerical computations of faceted pattern formation in snow crystal growth. Phys. Rev. E, 86, 011604, https://doi.org/10.1103/PhysRevE.86.011604, 2012.

(2) Definition of the natural sintering environment:

In this study, the *natural sintering environment* refers to placing the compacted specimen (still in the ring formwork, covered with a membrane on its surface, and surrounded by loose snow on its sides and top) in a temperature-controlled test chamber for sintering. This simulates the real conditions inside natural snow layer. When a snow specimen is directly exposed to air, its surface sublimates rapidly. In practical engineering, only the snow on the surface of a snow layer is directly exposed to air; the snow inside is not. Therefore, the authors spread snow around the ring formwork and over the upper and lower surfaces of the specimen to replicate the actual conditions. However, when the upper and lower surfaces were covered with snow, hydrogen bonding easily formed between the specimen surface and the external snow, leading to cementation. During sampling for testing, the specimen had to be separated from the surrounding snow, which inevitably disturbed the specimen. Therefore, a thin membrane was placed between the specimen and the surrounding snowflakes to isolate them. Based on the above explanation, the authors will revise and supplement the original content in the manuscript:

(2) Sintering: to simulate the natural sintering environment, a sealing membrane was

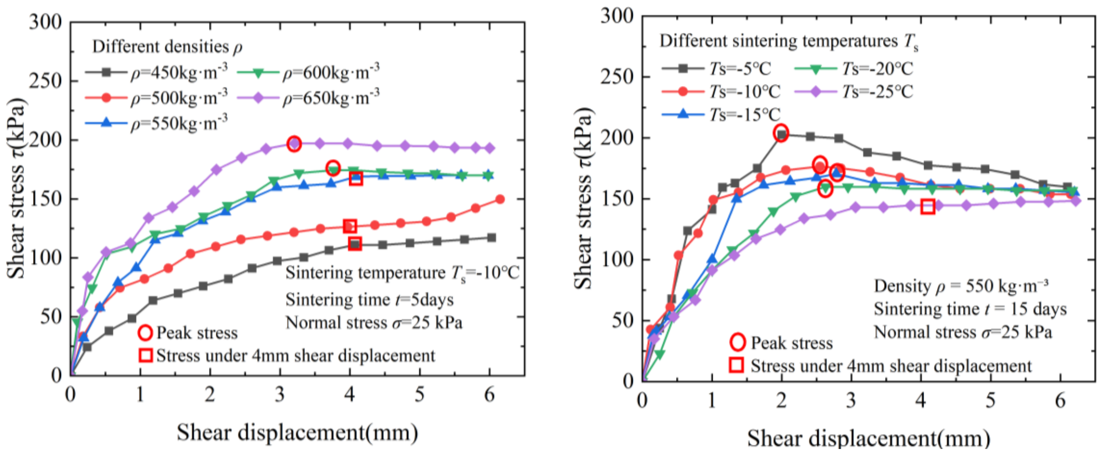
first placed over the compacted sample (still within the ring formwork). Uniform snowflakes were then spread around the sample and over the membrane to replicate the conditions inside snow layer. The surrounding snowflakes prevented rapid sublimation from exposed surfaces, while the membrane isolated the sample from the snow placed above it, thereby avoiding sintering bonding between the sample and the external snow. The entire assembly was then placed in a test chamber and sintered at the specified temperature for the designated duration.

Comment.4: Table 1: Please define σ as the other variables.

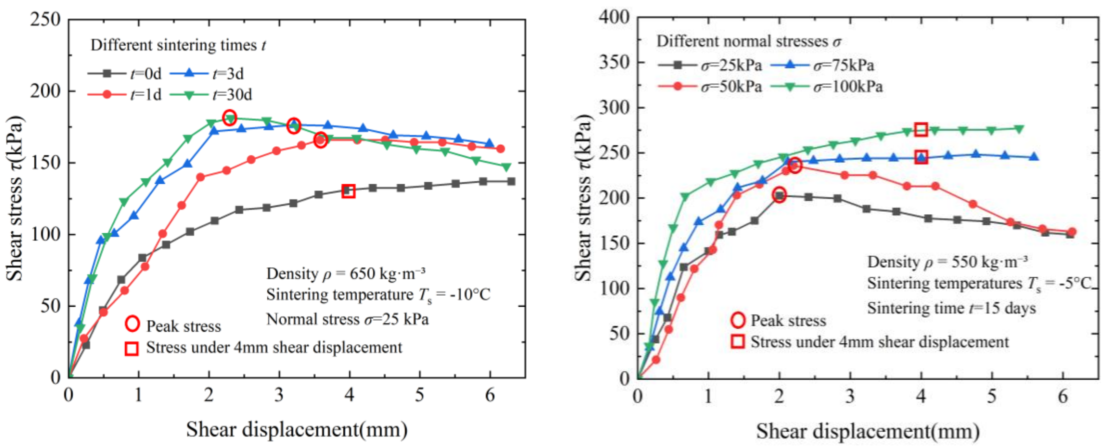
Response: Table 1 has been revised in the manuscript.

Comment.5: Figure 6: Please add the symbol definitions so the figure can be understood on its own.

Response: The corresponding symbol definitions have been added to the figure:



(a) (b)



(c) (d)

Figure 6: Shear stress–displacement curves under different test conditions ((a) Different densities; (b) Different sintering temperatures; (c) Different sintering times; (d)Different normal stresses).

Comment.6:157: This result is interesting, as lower densities closer to natural compacted snow often exhibit peak strain-softening. Why was 650 kg/m³ used for sintering time tests and 550 kg/m³ for sintering temperature tests?

Response: Thank you for your comment! The author has responded to each of the above questions:

(1) In Fig. 7 of the manuscript, the shear stress–displacement curves under different sintering temperatures show a peak region and a peak shear displacement. The variation trends for a density of 650 kg·m⁻³ and a density of 550 kg·m⁻³ are similar, both exhibiting a "step-like" distribution with normal stress and other variables. The density of 550 kg·m⁻³ was selected for the different sintering temperatures simply because the "step-like" trends was more pronounced under these two conditions, which better supports the authors' conclusion. Similarly, the specimens with a density of 450 kg·m⁻³ showed strain hardening under all sintering temperatures, so they were not plotted separately. In the figure below, panel (a) shows the original figure for different sintering temperatures (density 550 kg·m⁻³), and panel (b) shows an additional figure prepared by the authors for a density of 650 kg·m⁻³ under different sintering temperatures.

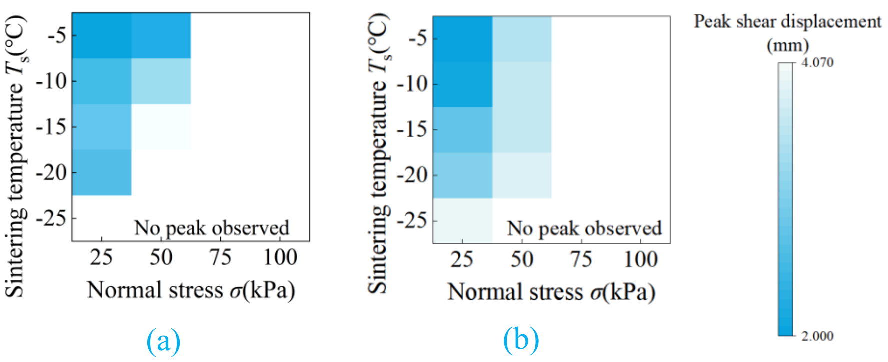


Figure 3: Development trends of shear stress–displacement curves under varying sintering temperatures ((a) 550 kg·m⁻³;(b) 650 kg·m⁻³)

(2) Regarding the strain-hardening and strain-softening behavior of the shear stress–displacement curves, it is widely accepted that shear rate is the dominant factor (McClung, 1977; De Montmollin, 1982; Puzrin et al., 2019). De Montmollin (1982) sheared snow samples with densities ranging from 180 to 430 kg·m^{-3} at different shear rates. He observed that a high shear rate induced brittle failure and strain softening, while a low shear rate led to ductile behavior and strain hardening. Notably, in De Montmollin's tests, for snow samples with a density of 300 kg·m^{-3} and a shear rate of 1.5 mm·min^{-1}, the samples still exhibited strain hardening despite the low density (see Fig. 5, redrawn from De Montmollin's data). This observation indicates that the effect of density on the failure mode is much smaller than that of shear rate. Therefore, even for the same density, changing the shear rate can alter the curve shape. Conversely, even for different densities, similar behavior may occur at the same shear rate.

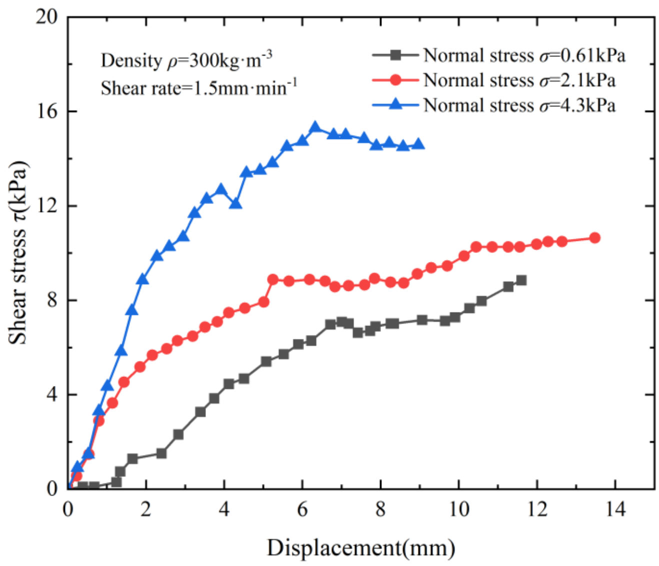


Figure 4: De Montmollin's experimental data (redrawn)

Based on the above, we consider that in this study, a shear rate of 0.8 mm·min^{-1} is relatively low for snow. Therefore, it is expected that strain hardening occurs under most test conditions. Only under specific combinations, such as high density, high degree of sintering, and low normal stress, does strain softening appear (Fig. 7 in the manuscript). This conclusion does not contradict previous studies; rather, it complements existing findings by showing that at a fixed shear rate, other influencing factors also affect the failure mode and the shape of the shear stress–displacement curve.

Comment.7:177: "…and increases again after 250 kg/m³."

Response: Thank you for your feedback! The relevant content has been revised in the manuscript.

Comment.8: Figure 11: Why is the density plotted with a dashed line while the other curves are solid? You should consider using dashed lines for all curves, since no observations exist outside the measured points and no analytical fit is provided.

Response: Thank you for your comment! The relevant figure has been revised in the manuscript:

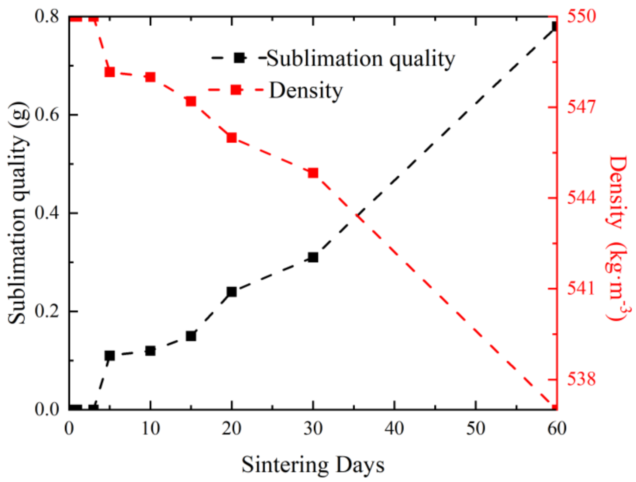


Figure 11: Variation of average sublimation mass and specimen density with different sintering times.

Comment.9: Section 4: Why use a neural network? It seems excessive for a four-variable input and a relatively simple interaction between variables.

Response: This issue has been addressed in the response to **Major Comment.1**. The authors have provided an explanation of the neural network in the manuscript.

Comment.10:284: Rephrase the sentence so it is clear that you compared the shear strength with all the other input variables.

Response: The sentence has been rephrased and clarified:

Fig. 19(a) presents the Spearman correlation coefficients between shear strength τ_f and each of the other input variables: normal stress σ, sintering temperature T_s, sintering time t, and density ρ.

Comment.11:337-339: Can you compare with other studies for your "low density"? It is surprising to me that you have no softening peak with lower densities that are closer to natural snow. Maybe discuss the influence of the other parameters on that matter (sintering time chose = 5 days).

Response: Thank you for your comment! The author has already addressed a similar issue in point (2) of comment.6.