Authors' Responses

Dear editor and reviewers:

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:

Responses to the comments of Editor：

The paper reports on interesting experimental results from a series of direct shear tests conducted on compacted snow samples. By systematically varying initial the density, sintering temperature and sintering time, the authors were able to gather a comprehensive dataset and investigate how the shear strength, cohesion and friction angle of their samples evolve with these parameters. They propose a neural network approach to fit the results and develop a predictive model for snow shear strength. This type of systematic mechanical testing on snow samples remains rare in the literature, and this study certainly provides a valuable and original contribution to the field. However, I believe that the paper needs to be improved in several areas prior to being considered for publication. In particular, I recommend addressing the following issues in the revision phase:

Comment.1: More details should be provided regarding the preparation and initial state of the samples: How is the initial compaction achieved? Does this compaction have an influence on the typical particle size (e.g., particle crushing)? Did the authors characterize the homogeneity of the initial state? What the role does the membrane used during sintering play? Does this membrane affect the sublimation effects reported later in the paper?

Response： The questions in this section will be answered one by one as follows:

(1) A cylindrical ring mold with an inner diameter of 61.8 mm and a height of 20 mm was used for compaction. Based on the target initial density (300–650 $kg \cdot m^{-3}$) and the fixed mold volume, the required snow mass for each specimen was calculated, and pre-weighed snow was evenly filled into the mold in layers. After each layer, a custom-made cylindrical tool (slightly smaller than the ring diameter) was used to compact the snow until the specimen was flush with the mold height. Compaction was applied manually at a slow, constant rate to ensure uniform stress distribution. Any specimens with visible cracks or uneven surfaces were discarded and re-prepared. All compaction operations were performed in a cold room at –10 °C.

(2) Compaction caused snowflakes to break into smaller particles, which filled the gaps between snowflakes and thereby increased density.

(3) During specimen preparation, an electronic balance with an accuracy of 0.01 g was used for weighing, and the density error of the specimens was controlled within 0.3 %. In addition, at least three parallel specimens were prepared for each test condition. The coefficient of variation (CV) was calculated to reflect the dispersion of the data, and error bars for the shear strength of parallel specimens were added to the manuscript. The results demonstrate good regularity in the variation of strength.

(4) When a snow specimen is exposed to the external environment, the surface in contact with the air sublimates rapidly. In practical engineering, the snow we test is inside the snow layer and does not directly contact the air. This experiment simulated real conditions: during sintering, the ring formwork was completely surrounded by snow, and the upper and lower surfaces of the specimen were also covered with snow, which easily led to hydrogen bonding and cementation between the specimen surface and the external snow. When preparing for the shear test, the specimen had to be separated from the surrounding snow, which inevitably disturbed the specimen. Therefore, a thin film was applied to the specimen to solve this problem. During

sintering, gas exchange between the specimen and the environment remained possible, but cementation with external snow was prevented.

Based on the above response, the author will revise and supplement the original content of the manuscript.

Revised: Lines 96 to 115:

(1) Compaction: A cylindrical ring formwork with an inner diameter of 61.8 mm and height of 20 mm was adopted for specimen preparation. Based on the target initial density ranging from 300 to 650 $kg \cdot m^{-3}$ and the fixed volume of the formwork, the required mass of snow for each specimen was calculated and pre-weighed using an electronic balance with an accuracy of 0.01 g, and the mass error was controlled within ±0.05 g. The snow was uniformly layered into the ring formwork, and compaction was conducted after each layer using a custom-made cylindrical tool (with a diameter slightly smaller than the formwork) to ensure homogeneous stress distribution. The compaction force was applied manually at a slow and constant rate until the specimen surface was level with the top of the ring formwork. During compaction, snow grains were partially fractured to generate finer particles that filled intergranular voids, thereby increasing the specimen density. Any specimen with visible cracks or surface irregularities was discarded and re-prepared. At least three parallel specimens were prepared for each test condition, and all compaction procedures were performed in a −10 °C cold chamber. The prepared compacted specimen is presented in Fig. 1(a).

(2) Sintering: to simulate the natural sintering environment, a sealing membrane was placed over the compacted specimen while it remained inside the ring formwork. Uniform snowflakes were then distributed around the specimen and across the membrane to replicate the in-situ conditions within a natural snowpack. The surrounding snowflakes mitigated rapid sublimation from exposed surfaces, whereas the membrane isolated the specimen from the overlying snow, thus preventing unintended sintering bonding between the specimen and external snow. The entire assembly was subsequently placed in a temperature-controlled test chamber and sintered at the prescribed temperature for the designated duration. Specimens covered with sealing membranes are shown in Fig. 1(b), and snowflakes deposited on the

specimens and membranes are presented in Fig. 1(c).

(a) (b) (c)

Figure 1: Sample preparation process ((a) Compacted specimen; (b) Samples covered with membranes; (c) Sprinkling snowflakes).

Comment.2： Computing a strain rate from the displacement velocity seems artificial, given that shear deformation is highly localized in this setup. In fact, the actual strain rate in the sheared layer is probably much higher than an average value. Therefore, the gray band in Fig. 4 probably does not provide much information about the true deformation regime undergone by the samples.

Response: Thank you for raising this important question regarding the strain rate calculation in the tests. In the direct shear tests, analyzing the shear stress–shear displacement curves alone were sufficient for the investigation of strength parameters in the study. The authors converted shear displacement into shear strain solely for the purpose of comparison with Figure 4. Regarding Figure 4, it is cited from Puzrin et al. (2019), who synthesized several experimental studies on the relationship between shear rate and snow shear strength and identified a general trend: shear strength first increases with shear rate, reaches a peak, and then decreases, with a transition zone (the grey band in Figure 4) corresponding to the ductile-brittle transition.

Our intention in citing this figure was:

(1) To illustrate the qualitative trend between snow strength and shear rate;

(2) To provide a reference background for the present test conditions, showing where the shear rate (shear strain rate) used in our tests falls in comparison with previous studies; and

(3) To acknowledge that the strength parameters obtained in this study are related to the specific shear rate used, and to propose that the rate employed in our tests can serve as a reference for repeatability and comparison in future studies by other researchers.

Comment.3： More details should be provided on test reproducibility and measurement errors, and error bars should be added to the plots. This is essential for any experimental study. Otherwise, the observed trends can always be called into question.

Response： Thank you for your suggestion. The authors will add the coefficient of variation (CV) to the manuscript. In addition, the mean and standard deviation of the shear strength measured from all parallel tests will be supplemented in the manuscript, together with the standard deviations of cohesion and internal friction angle fitted by the least squares method based on the mean values.

Revised:

(1) Lines 158 to 165:

For each test condition, three parallel specimens were tested, and the average shear strength was calculated. The coefficient of variation (*CV*) is a widely used index for quantifying the dispersion of snow strength (Jamieson and Johnston, 2001; Perla, 1977; Sommerfeld and King, 1979). In this study, CV was used to evaluate the dispersion of the measured strength values, which was calculated as follows:

$$CV = \frac{s}{\overline{\tau}_{\mathrm{f}}} \tag{1}$$

where s is the standard deviation and $\overline{\tau}_{\mathrm{f}}$ is the mean of the three parallel strength values.

Fig. 6 presents the distribution of *CV* values for all specimens. The *CV* was below 20% for most specimens and did not exceed 30% for any specimen, indicating that the specimens possessed relatively good uniformity.

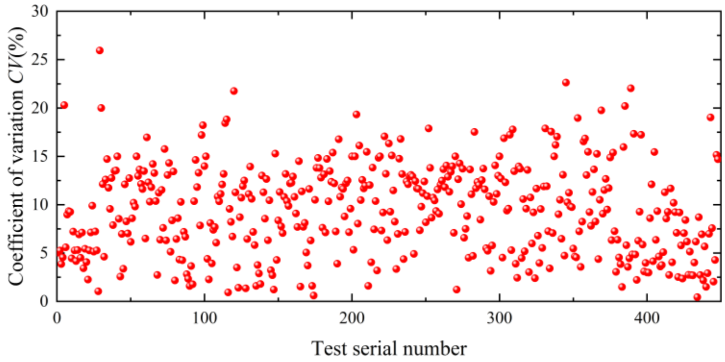

Figure 6: Coefficients of variation for all test samples.

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(2) Lines 168 to 171:

Based on the test results, the mean values and standard deviations of shear strength for the three parallel specimens under each condition were plotted. According to the linear Mohr–Coulomb criterion (Eq. 2), the cohesion *c* and internal friction angle *φ* were determined using the least squares method, and the error bars of *c* and *φ* were plotted based on the fitting results.

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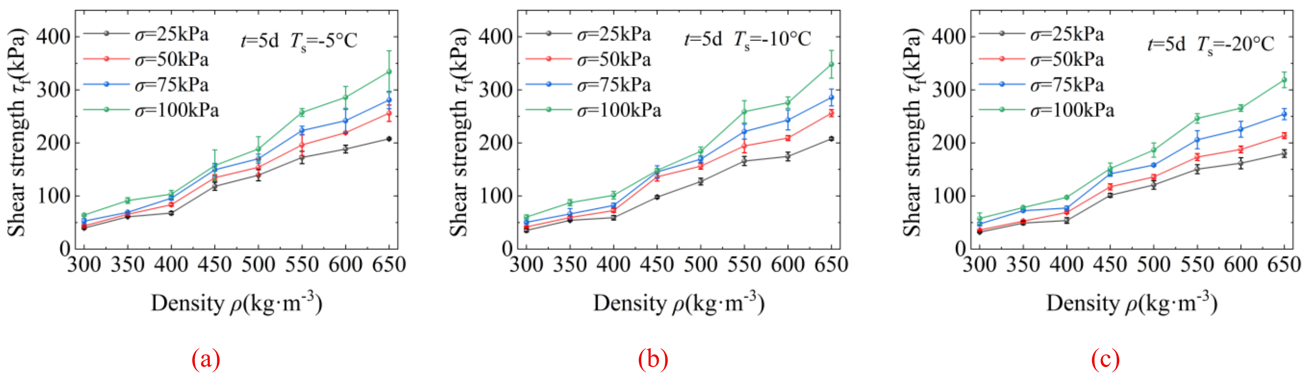


Figure 9: Variation of shear strength with initial density under different normal stresses after 5 days ((a)T_s=-5 °C; (b) T_s=-10 °C; (c) T_s=-20 °C).

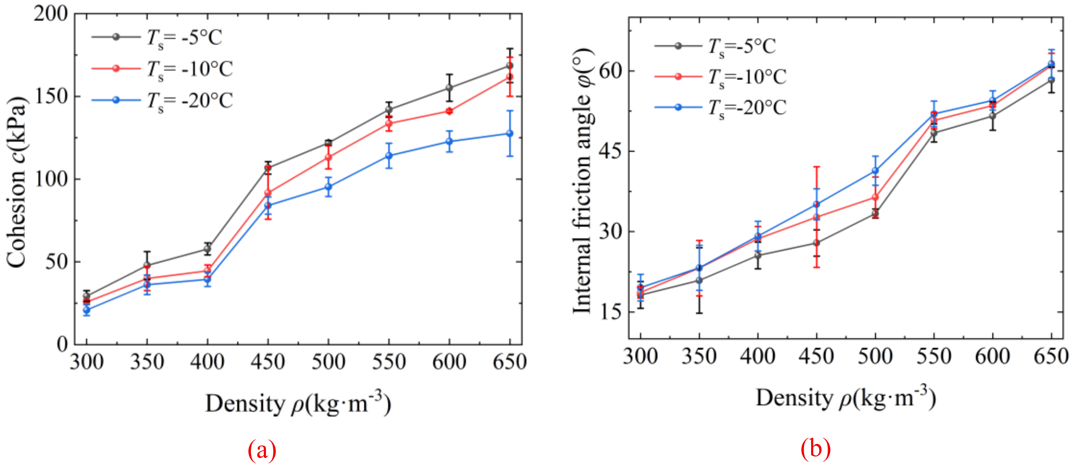


Figure 10: Variation of shear strength parameters at different initial densities after 5 days ((a) Cohesion *c*; (b) Internal friction angle *φ*).

Reference:

Jamieson, B. and Johnston, C. D.: Evaluation of the shear frame test for weak snowpack layers, Ann. Glaciol., 32, 59–69, https://doi.org/10.3189/172756401781819472, 2001.

Perla, R.: Slab avalanche measurements, Can. Geotech. J., 14, 206–213, https://doi.org/10.1139/t77-021, 1977.

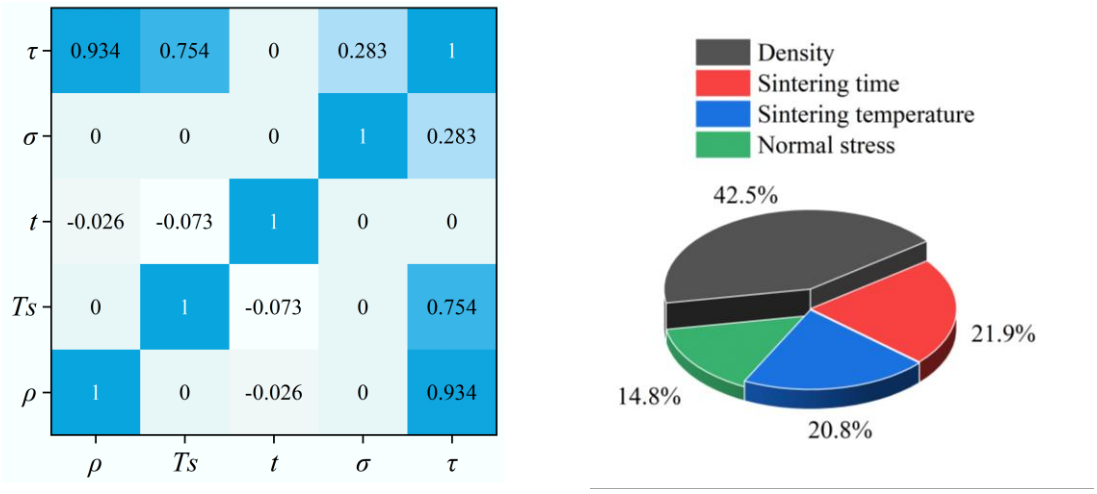
Sommerfeld, R. A. and King, R. M.: A recommendation for the application of the Roch index for slab avalanche release, J. Glaciol., 22(88), 547–549, https://doi.org/10.1017/s0022143000014520,1979.

Comment.4： The objectives and outcomes of the neural network model should be explained and discussed more clearly. What can be learnt from the predicted values shown in Figs. 21 and 22, that was not already apparent in the experimental data? What is the applicability of the model? Given that it was trained on a single type of snow grain, and for a single value of displacement rate, its capability to predict strength parameters in a wide range of contexts relevant to the design and construction of compacted snow structures is probably to be nuanced.

Response： The authors provide point-by-point responses as follows:

(1) Objective and results of the neural network:

The neural network model in this study was established based on the following considerations. It aimed to capture the nonlinear relationships between the four input variables (density, sintering time, sintering temperature, normal stress) and the shear strength. For example, the effect of sintering time on strength depends on the sintering temperature (higher temperature leads to faster sintering). As the sintering time increases from 0 to 60 days, the strength exhibits a highly nonlinear trend of first increasing and then decreasing, which is difficult to accurately express using traditional fitting functions. Furthermore, by using the connection weight method, the model quantified the relative importance of each factor (Fig. 19(b): density 42.5 %, sintering time 21.9 %, normal stress 20.8 %, sintering temperature 14.8 %). Such parameters are not easily obtainable directly from experimental data alone.



(a) (b)

Figure 19: Analysis of model parameters ((a) Spearman's correlation coefficient matrix; (b) Relative importance of each parameter).

(2) Information shown in Figs. 21 and 22:

Figs. 21 and 22 present the continuous variation surfaces of cohesion c and internal friction angle φ, respectively, under different combinations of density, sintering time, and sintering temperature. These surfaces more intuitively illustrate the interactions among the parameters and their combined effects on the strength parameters. Such multi-dimensional visualization of strength parameters provides a more comprehensive reference for engineering applications than discrete data points alone.

(3) Applicability and limitations:

Since this study considered only one shear rate and one snow type, whereas engineering practice involves more complex environmental factors, the strength parameters under different conditions should be adjusted through experimental investigations, using the values obtained in this study as a benchmark. For example, when considering factors such as shear rate and normal stress, the relationship between the strength parameters under different conditions and those in this study can be obtained experimentally, and then quantitative adjustments can be made based on the strength parameters provided herein.

The core contribution of this paper is not only the results under the current conditions but also a reusable modeling framework, which lays the foundation for future extensions to a wider range of conditions. Corresponding content has been supplemented in the manuscript.

Revised:

(1) Objectives and Results of Neural Networks (Lines 288 to 295):

4 Prediction Using GA-BP Neural Network

As demonstrated in Chapter 3, the effects of various influencing factors on shear strength are characterized by complex interactions and nonlinear relationships. Such behaviors are difficult to characterize accurately using conventional function-fitting methods. By comparison, neural networks exhibit superior capability in processing nonlinear data. To quantitatively identify 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.

(2) Add the applicability and limitations of neural network models to the discussion (Lines 439 to 451):

4.3.3 Highlights and limitations of this study

Combining laboratory experiments and a neural network model, this study established baseline direct shear strength parameters for compacted snow covering a range of influencing conditions: an initial density of 300 to 650 kg·m^{-3}, sintering temperature of -25 to -5 °C, sintering duration of 0 to 60 days, and normal stress of 25 to 100 kPa. The derived baseline parameters can provide a reference for engineers to conduct deformation analysis, bearing capacity evaluation, and stability calculation of snow-based infrastructures in polar and cold regions. When snow type or environmental conditions vary, updated strength parameters can be acquired via laboratory testing. By further establishing the quantitative correlation between newly measured parameters and the baseline values proposed in this study, targeted correction of the existing baseline data can be realized.

This study solely considered four influencing factors, namely initial density, sintering temperature, sintering time, and normal stress within the range of 25 to 100 kPa, with a fixed shear loading rate of 0.8 mm·min^{-1}. The evolution characteristics of the shear strength parameters of compacted snow under additional internal and external influencing factors remain to be explored in future research. Key internal factors include snow type, liquid water content, and particle size distribution, while major external factors cover ambient humidity, specimen sealing conditions, loading rate, and extended normal stress levels.

Comment.5: The discussion section should be expanded and written in a more literary style, avoiding bullet-point-style writing. In particular, comparisons with previous studies, the applicability and limits of the model, and the overall significance of the results need to be discussed more thoroughly. The conclusions that can be drawn from the study need to be distinguished more clearly from general considerations stemming from the literature.

Response: The author has rewritten the discussion section.

Revised: (Lines399 to 451):

4.3 Discussion

4.3.1 Physical mechanisms governing the evolution of direct shear strength parameters

Initial density is the dominant factor governing the direct shear strength and mechanical strength parameters of compacted snow. An increase in density creates more interparticle contact points per unit volume and yields a denser internal microstructure (Butkovich, 1958; Mellor, 1977), which strengthens intergranular bonding and frictional interlocking. As illustrated in Fig. 11, both cohesion and internal friction angle rise markedly as the initial density increases from 300 to 650 kg·m^{-3}. Under a sintering temperature of -10 °C and a sintering duration of 5 days, cohesion increases from 25.73 to 161.85 kPa, while the internal friction angle grows from 18.65° to 60.98°.

The shear strength evolution of compacted snow with sintering time is governed by the coupled effects of sublimation and the formation of interparticle hydrogen bonds during sintering. In the early sintering stage, hydrogen bonds form rapidly between snow grains, whereas the density attenuation induced by sublimation remains insignificant, resulting in a rapid rise in shear strength. Subsequently, the sintering process gradually stabilizes, accompanied by sustained density reduction. Controlled by the interplay of these two mechanisms, the shear strength fluctuates slightly and maintains a relatively stable level. As sintering time further prolongs, sublimation gradually dominates the structural evolution, leading to a continuous decline in shear strength.

During sintering, the protrusions on snow grain surfaces undergo preferential sublimation, rendering particle morphologies more regular (Bahaloo et al., 2024; Colbeck, 1983a; Paterson, 1994; Wang, 1982; Zhuang, 2019). This smoothens particle surface roughness and consequently induces a gradual reduction in the internal friction angle. By contrast, cohesion exhibits a variation trend consistent with that of shear strength, rising initially and then declining slowly. Taking the specimen with a density of 550 kg·m^{-3} sintered at -10 °C as an example (Fig. 14), as sintering time extends to 60 days, cohesion first increases from 53.54 to 141.85 kPa and then decreases to 131.99 kPa; meanwhile, the internal friction angle drops from 52.78° to 38.58°.

Elevated sintering temperature intensifies the Brownian motion of water vapor, which promotes the formation of hydrogen bonds among snow particles (Abele, 1967, 1990;

Colbeck, 1983a). A higher sintering degree further reinforces interparticle bonding and regularizes grain surface morphology. As shown in Fig. 15, when the sintering temperature rises from -25 to -5 °C, cohesion increases considerably. For specimens with a density of 550 kg·m^{-3} sintered for 15 days, cohesion increases from 115.4 to 183.72 kPa, while the internal friction angle decreases from 48.69° to 41.74°.

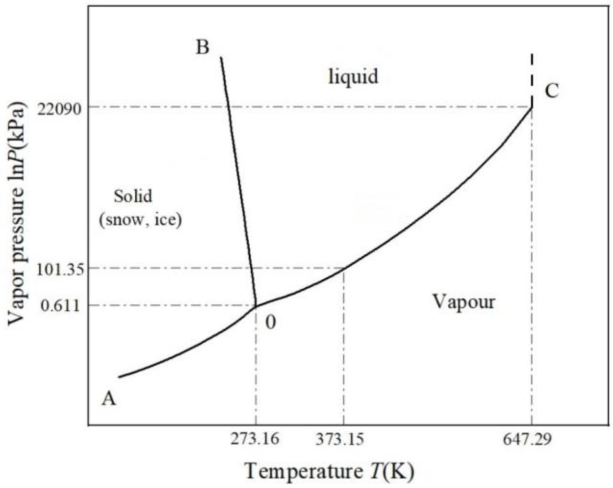


Figure 24: Phase diagram of water (A denotes the sublimation line, B denotes the melting line, and C denotes the evaporation line).

4.3.2 Comparison with existing studies

This study systematically investigated the variation patterns of shear strength and its key parameters of compacted snow, with a focus on the effects of three critical factors: initial density, sintering time, and sintering temperature. The influences of initial density and sintering temperature observed in this study are consistent with the findings of previous research (Butkovich, 1958; Ballard et al., 1965; Perla & Beck, 1982; Schweizer, 1998). With respect to the effect of sintering time, similar conclusions have been corroborated by both field investigations and laboratory experiments (Jellinek, 1959; Zhuang, 2019; Fu, 2020; Yang, 2024).

In contrast, Abele (1990) reported that the sintering strength of snow continued to increase without exhibiting a decreasing trend. However, the experimental details (e.g., ambient humidity and specimen sealing conditions) were not clearly described in that study, which may have led to discrepancies in the observed results. Therefore, more refined and controlled experiments are required in future research to further clarify and verify the strength variation patterns of compacted snow.

4.3.3 Highlights and limitations of this study

Combining laboratory experiments and a neural network model, this study established baseline direct shear strength parameters for compacted snow covering a range of influencing conditions: an initial density of 300 to 650 $kg \cdot m^{-3}$, sintering temperature of -25 to -5 °C, sintering duration of 0 to 60 days, and normal stress of 25 to 100 kPa. The derived baseline parameters can provide a reference for engineers to conduct deformation analysis, bearing capacity evaluation, and stability calculation of snow-based infrastructures in polar and cold regions. When snow type or environmental conditions vary, updated strength parameters can be acquired via laboratory testing. By further establishing the quantitative correlation between newly measured parameters and the baseline values proposed in this study, targeted correction of the existing baseline data can be realized.

This study solely considered four influencing factors, namely initial density, sintering temperature, sintering time, and normal stress within the range of 25 to 100 kPa, with a fixed shear loading rate of 0.8 $mm \cdot min^{-1}$. The evolution characteristics of the shear strength parameters of compacted snow under additional internal and external influencing factors remain to be explored in future research. Key internal factors include snow type, liquid water content, and particle size distribution, while major external factors cover ambient humidity, specimen sealing conditions, loading rate, and extended normal stress levels.

References:

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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.

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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.

Responses to the comments of Reviewer#1：

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 Linesar) with only 4 input variables. Usually, neural networks are chosen for non-Linesar 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.

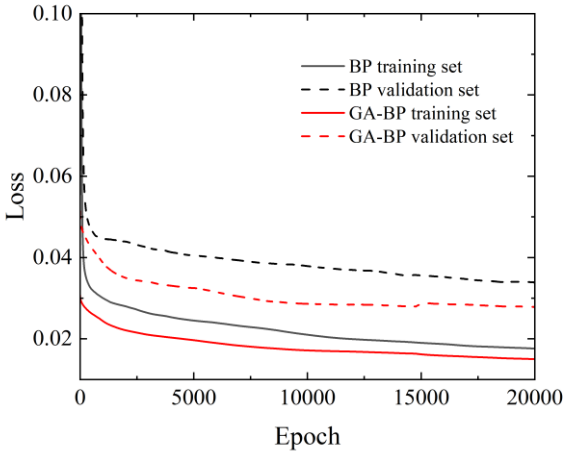

Figure 1: Epoch-loss curve

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 study. At the very least, there is no serious overfitting problem.

Corresponding content has been added to the original manuscript.

Revised:

(1) Lines 288 to 295:

4 Prediction Using GA-BP Neural Network

As demonstrated in Chapter 3, the effects of various influencing factors on shear strength are characterized by complex interactions and nonlinear relationships. Such behaviors are difficult to characterize accurately using conventional function-fitting methods. By comparison, neural networks exhibit superior capability in processing nonlinear data. To quantitatively identify 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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(2) Lines 298 to 299:

4.1.1 Data Collection and Preprocessing

A total of 448 experimental data points were obtained, among which 70% were randomly assigned to the training set, 15% to the validation set, and the remaining 15% to the test set……

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(3) Lines 344 to 347:

4.2.2 Neural Network Prediction Results

Upon completion of neural network training, 15% of the total dataset (67 samples), excluded from the training process, was randomly assigned as the test set. The predictive accuracy of the trained neural network was subsequently assessed by comparing the model-predicted values with the experimental measured data……

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.

Revised: Lines399 to 451:

4.3 Discussion

4.3.1 Physical mechanisms governing the evolution of direct shear strength parameters

Initial density is the dominant factor governing the direct shear strength and mechanical strength parameters of compacted snow. An increase in density creates more interparticle contact points per unit volume and yields a denser internal microstructure (Butkovich, 1958; Mellor, 1977), which strengthens intergranular bonding and frictional interlocking. As illustrated in Fig. 11, both cohesion and internal friction angle rise markedly as the initial density increases from 300 to 650 kg·m^{-3}. Under a sintering temperature of -10 °C and a sintering duration of 5 days, cohesion increases from 25.73 to 161.85 kPa, while the internal friction angle grows from 18.65° to 60.98°.

The shear strength evolution of compacted snow with sintering time is governed by the coupled effects of sublimation and the formation of interparticle hydrogen bonds during sintering. In the early sintering stage, hydrogen bonds form rapidly between snow grains, whereas the density attenuation induced by sublimation remains insignificant, resulting in a rapid rise in shear strength. Subsequently, the sintering process gradually stabilizes, accompanied by sustained density reduction. Controlled by the interplay of these two mechanisms, the shear strength fluctuates slightly and maintains a relatively stable level. As sintering time further prolongs, sublimation gradually dominates the structural evolution, leading to a continuous decline in shear strength.

During sintering, the protrusions on snow grain surfaces undergo preferential sublimation, rendering particle morphologies more regular (Bahaloo et al., 2024; Colbeck, 1983a; Paterson, 1994; Wang, 1982; Zhuang, 2019). This smoothens particle surface roughness and consequently induces a gradual reduction in the internal friction angle. By contrast, cohesion exhibits a variation trend consistent with that of shear strength, rising initially and then declining slowly. Taking the specimen with a density of 550 kg·m^{-3} sintered at -10 °C as an example (Fig. 14), as sintering time extends to 60 days, cohesion first increases from 53.54 to 141.85 kPa and then decreases to 131.99 kPa; meanwhile, the internal friction angle drops from 52.78° to 38.58°.

Elevated sintering temperature intensifies the Brownian motion of water vapor, which promotes the formation of hydrogen bonds among snow particles (Abele, 1967, 1990; Colbeck, 1983a). A higher sintering degree further reinforces interparticle bonding and regularizes grain surface morphology. As shown in Fig. 15, when the sintering temperature rises from -25 to -5 °C, cohesion increases considerably. For specimens with a density of 550 kg·m^{-3} sintered for 15 days, cohesion increases from 115.4 to 183.72 kPa, while the internal friction angle decreases from 48.69° to 41.74°.

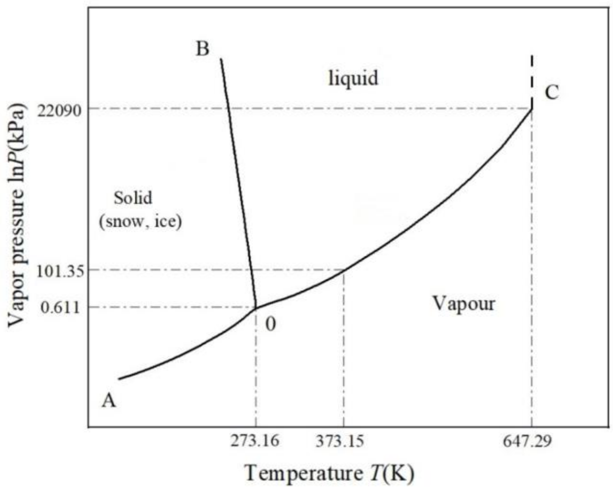


Figure 24: Phase diagram of water (A denotes the sublimation line, B denotes the melting line, and C denotes the evaporation line).

4.3.2 Comparison with existing studies

This study systematically investigated the variation patterns of shear strength and its key parameters of compacted snow, with a focus on the effects of three critical factors: initial density, sintering time, and sintering temperature. The influences of initial density and sintering temperature observed in this study are consistent with the findings of previous research (Butkovich, 1958; Ballard et al., 1965; Perla & Beck, 1982; Schweizer, 1998). With respect to the effect of sintering time, similar conclusions have been corroborated by both field investigations and laboratory experiments (Jellinek, 1959; Zhuang, 2019; Fu, 2020; Yang, 2024).

In contrast, Abele (1990) reported that the sintering strength of snow continued to increase without exhibiting a decreasing trend. However, the experimental details (e.g., ambient humidity and specimen sealing conditions) were not clearly described in that study, which may have led to discrepancies in the observed results. Therefore, more refined and controlled experiments are required in future research to further clarify and verify the strength variation patterns of compacted snow.

4.3.3 Highlights and limitations of this study

Combining laboratory experiments and a neural network model, this study established baseline direct shear strength parameters for compacted snow covering a range of influencing conditions: an initial density of 300 to 650 kg·m^{-3}, sintering temperature of -25 to -5 °C, sintering duration of 0 to 60 days, and normal stress of 25 to 100 kPa. The derived baseline parameters can provide a reference for engineers to conduct deformation analysis, bearing capacity evaluation, and stability calculation of snow-based infrastructures in polar and cold regions. When snow type or environmental conditions vary, updated strength parameters can be acquired via laboratory testing. By further establishing the quantitative correlation between newly measured parameters and the baseline values proposed in this study, targeted correction of the existing baseline data can be realized.

This study solely considered four influencing factors, namely initial density, sintering temperature, sintering time, and normal stress within the range of 25 to 100 kPa, with a fixed shear loading rate of 0.8 mm·min^{-1}. The evolution characteristics of the shear strength parameters of compacted snow under additional internal and external influencing factors remain to be explored in future research. Key internal factors include snow type, liquid water content, and particle size distribution, while major external factors cover ambient humidity, specimen sealing conditions, loading rate, and extended normal stress levels.

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 (Lines 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 Lines 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.

Revised: Lines 80 to 84:

Machine-made snow was artificially produced to prepare high-density specimens, which was generated via atomization, cooling, and crystallization processes, closely replicating the natural snow formation mechanism (Dong et al., 2023). During snow production, a high-pressure pump within the snowmaking machine pressurized water to 6 MPa, and the pressurized water was subsequently atomized into fine droplets through a custom-designed nozzle (Kang et al., 2018; Vijay et al., 2015).

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.

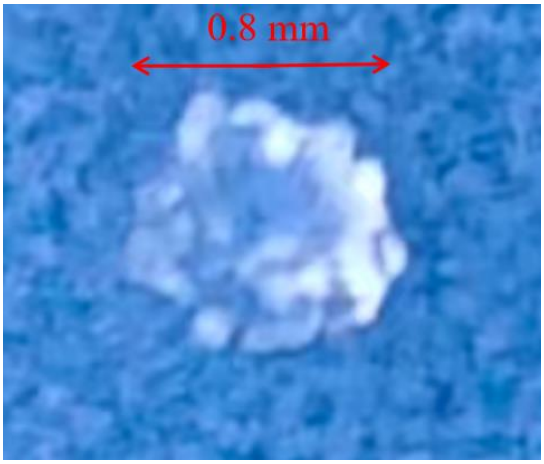


Figure 1: Morphology and size of experimental snow

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).

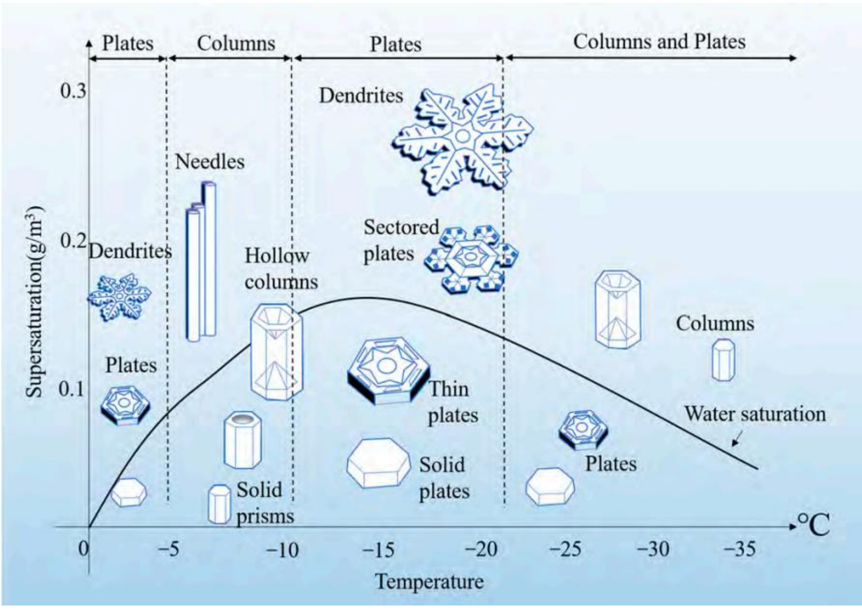


Figure 2: Classification of snow morphology (Barrett et al., 2012)

The relevant content has been revised:

Revised: Lines 90 to 94:

both machine-made snow and natural snow were immediately transported to a cold storage chamber with a temperature of -10 ° C and relative humidity of 60 % for prompt specimen preparation. Both snow types exhibited comparable physical properties. The initial density of natural snow was approximately 200 kg •m^{-3} , whereas that of machine-made snow was around 300 kg • m^{-3} . Following the classification by Barrett et al. (2012), the snow crystals were plate-like, with particle sizes ranging approximately from 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.

Revised: Lines 107 to 112:

(2) Sintering: to simulate the natural sintering environment, a sealing membrane was placed over the compacted specimen while it remained inside the ring formwork. Uniform snowflakes were then distributed around the specimen and across the membrane to replicate the in-situ conditions within a natural snowpack. The surrounding snowflakes mitigated rapid sublimation from exposed surfaces, whereas the membrane isolated the specimen from the overlying snow, thus preventing unintended sintering bonding between the specimen and external snow. The entire assembly was subsequently placed in a temperature-controlled test chamber and sintered at the prescribed 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.

Revised:

Table 1 Test conditions.

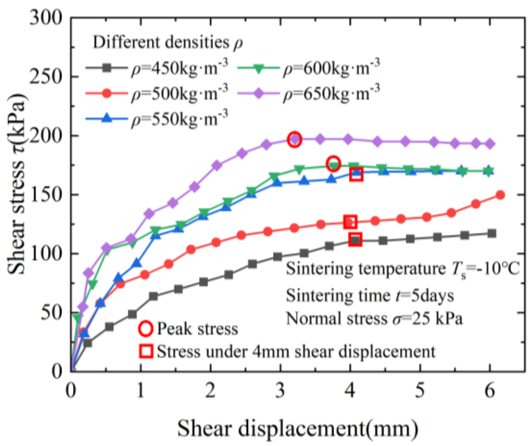
Serial number	ρ（$kg\cdot m^{-3}$）	t（days）	T_s（℃）	Other variables
D-1	300,350,400,450,500,550,600,650	5	-5	σ=25,50,75,100 kPa
D-2	300,350,400,450,500,550,600,650	5	-10	σ=25,50,75,100 kPa
D-3	300,350,400,450,500,550,600,650	5	-20	σ=25,50,75,100 kPa
t-1	300	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-2	350	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-3	400	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-4	450	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-5	550	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-6	650	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
T-1	300	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-2	350	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa

T-3	400	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-4	450	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-5	550	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-6	650	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
H-1	300	1,30	-5, -20	σ=25,50,75,100 kPa
H-2	350	1,30	-5, -20	σ=25,50,75,100 kPa
H-3	400	1,30	-5, -20	σ=25,50,75,100 kPa
H-4	550	1,30	-5, -20	σ=25,50,75,100 kPa

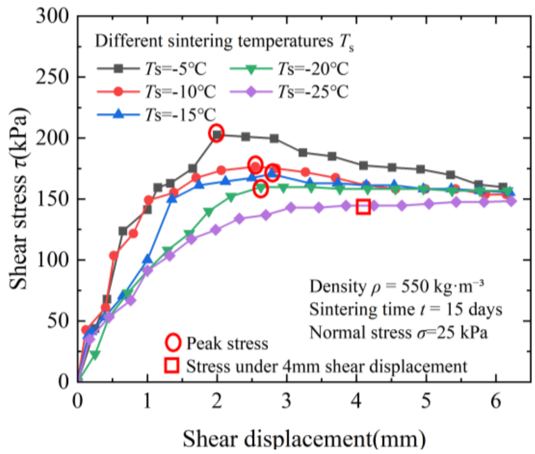
Comment.5: Figure 6: Please add the symbol definitions so the figure can be understood on its own.

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

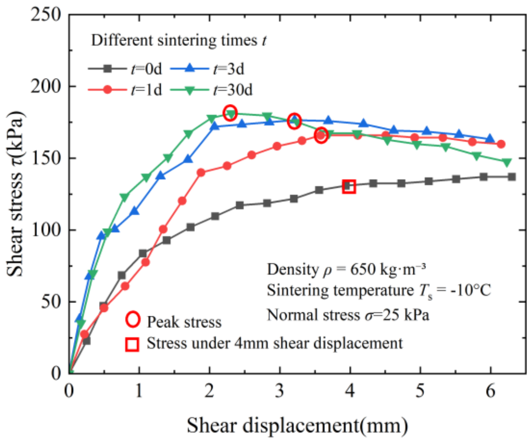
Revised:

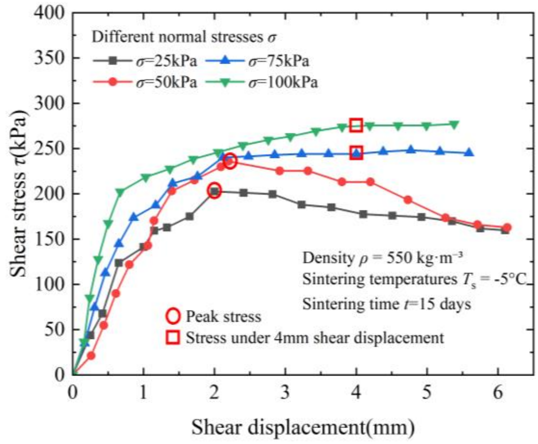


(a)



(b)





(c) (d)

Figure7: 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: L157: 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.

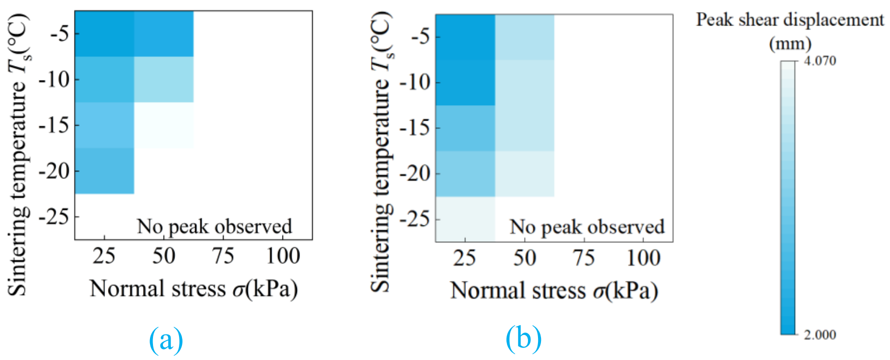


Figure 3: Development trends of shear stress–displacement curves under varying sintering temperatures ((a) 550 kg·m⁻³;(b) 650 kg·m⁻³)

(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 $kg \cdot m^{-3}$ 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 $kg \cdot m^{-3}$ and a shear rate of 1.5 $mm \cdot min^{-1}$, 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.

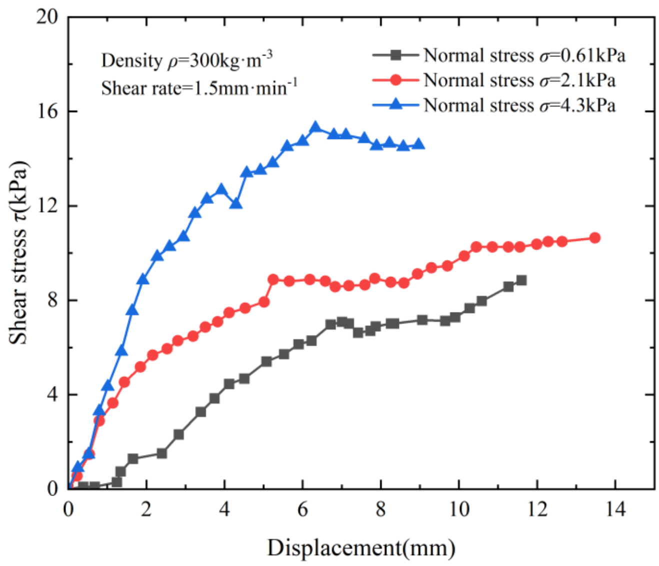


Figure 4: De Montmollin's experimental data (redrawn)

Based on the above, we consider that in this study, a shear rate of 0.8 $mm \cdot min^{-1}$ 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.

Revised: Lines 222 to 225: It is evident that for snow samples with varying densities and in unsintered conditions, the shear strength increases linearly with normal pressure up to 100 kPa. Beyond this threshold, the rate of increase in shear strength diminishes, and increases again after 250 kPa, indicating nonlinear behavior.

Comment.8: Figure 11: Why is the density plotted with a dashed Lines while the other curves are solid? You should consider using dashed Liness 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.

Revised:

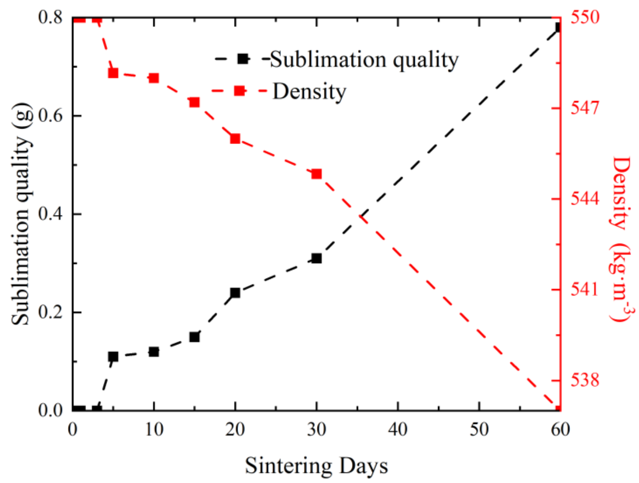


Figure 12: Variation of average sublimation mass and specimen density with different sintering times.

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.

Revised: Lines 332 to 333:

Fig. 19(a) presents the Spearman correlation coefficients between shear strength τ_f and each input variable, namely 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.

Responses to the comments of Reviewer#2：

Summary

This manuscript presents methods, datasets, and results from a laboratory experiment related to the shear strength of compressed snow cylinders, where snow samples were obtained from an artificially created snowpack. The findings of this study could have significance for cold regions structural engineering applications, where infrastructure is built from compressed snow, and therefore stability of said infrastructure is highly dependent upon shear and normal strength of various snowpack types. Methods from the study include both an empirical approach involving laboratory testing, as well as a modeling approach, using a neural prediction network. Results of the two approaches include an observational dataset, as well as simulated model output, respectively.

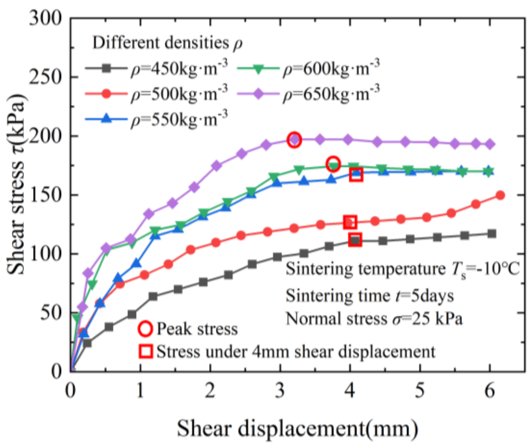
The model was calibrated and validated via partitioning of the empirically derived data. Four parameters were varied and tested in different combinations, using an applied horizontal shear force held constant for each variation of the other parameters. The varied parameters included initial compaction density, applied normal force, snow crystal sintering time, and sintering temperature. Internal friction angle and cohesion of the various samples were calculated using a previously established algorithm from the literature.

The approach and results of this study are interesting and a valuable contribution to snow physics and mechanics, although the overall novelty of this experiment is limited. If the methods presented here can be replicated in future experiments, results from multiple studies could eventually provide a statistically significant body of evidence for establishing numerical thresholds for these snow shear strength parameters. Such thresholds would be valuable for practical use in snow engineering.

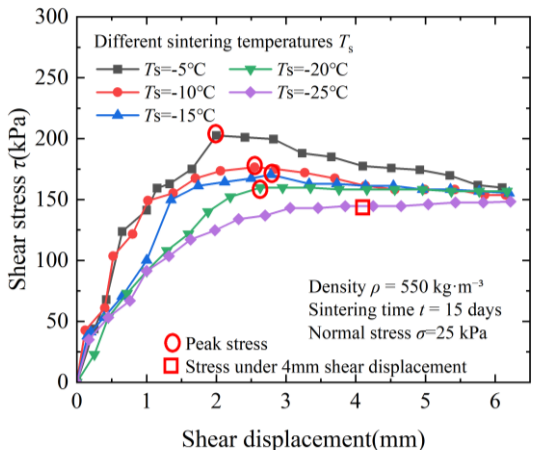
Comment R2.1 (Overall): Shear Stress vs Shear Strength: The authors use these words somewhat interchangeably; however, these are not really the same thing. Conceptually related, but distinct, shear stress is the internal force per unit area acting within a material due to external loads, while strength is the maximum stress said material can withstand before failure (plastic deformation). For this study, stress is the demand placed on each snow sample, while strength is the capacity of each sample. A material fails when the applied stress equals or exceeds its strength. This is commonly a grey area within the field of snow mechanics, because shear stress is a quantifiable variable with established units of measurement, while shear strength is more nebulous. Previous studies offer approaches for defining snow strength, but it is overall still more of a concept than it is a specific quantity. While sometimes perplexing, defining snow strength is still an open field of research with much opportunity for creativity.

Response: Thank you very much for your valuable comment. The author has corrected the instances where shear stress and shear strength were used interchangeably in the original manuscript.

Revised:



(a)



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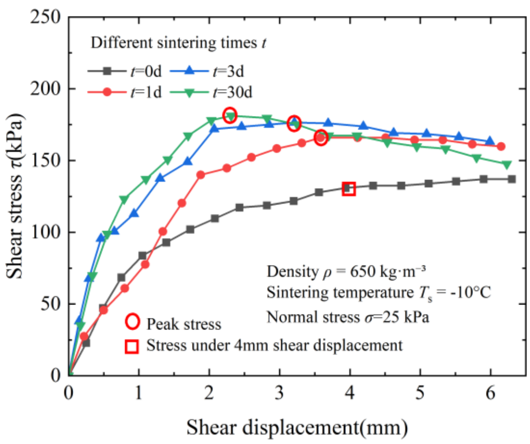
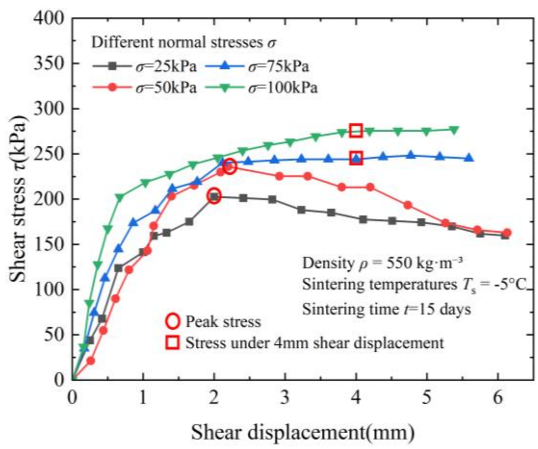


(c)



(d)

Figure 7: Shear stress–displacement curves under different test conditions ((a) Different densities; (b) Different sintering temperatures; (c) Different sintering times; (d)Different normal stresses).

Comment R2.2 (Overall):

Abstract: Add a little more context (a couple sentences here) and briefly describe the conditions of the experiment. It would be easier to understand the summary of results and what the paper is about, with a simple description of the experiment set up, i.e., "experiments were conducted in a cold lab with environmental controls, using an instrument that does…." Which parameters were measured vs. calculated vs. modeled? Specify which parameters are the "essential strength parameters".

Response: Thank you for your comment. The abstract has been updated accordingly.

Revised: Lines 12 to 21:

Abstract. ……Direct shear tests were carried out on low-density natural snow and high-density artificial snow in a -10 °C cold laboratory. In total, 112 test conditions were designed to quantify the effects of initial density, sintering time and sintering temperature on shear strength parameters at normal stresses below 100 kPa…… A Genetic Algorithm-Back Propagation (GA-BP) neural network was utilized to construct a shear strength prediction model, taking density, sintering time, sintering temperature, and normal stress as inputs, and offering benchmark values for cohesion and internal friction angle under various conditions.

Comment R2.3 (Overall):

Introduction: I don't fully agree with the first part of the last paragraph in this section. I'm not sure that most previous studies within the snow engineering field of research are, in fact, focused on low density snow. I'd say the opposite is true. Most engineering related snow research actually does focus on compacted/altered snow, while avalanche research typically explores unaltered/natural, in-situ snowpacks. Either way, citations of studies on low density snow strength for snow engineering purposes should be provided. Or consider removing this section.

Response: Thank you for your comment. The author has added experiments on low-density snow in the range of 300 to 400 kg·m^{-3}. Additionally, the wording in that section of the introduction has been revised accordingly.

Revised: Lines 62 to 67:

Previous snow avalanche studies have mainly focused on low-density natural snow (McClung, 1977; Schweizer, 1998), whereas engineering-oriented investigations have concentrated on compacted or artificially modified snow (Sun et al., 2021; White and McCallum, 2020; White, 2023). Although the shear strength of snow has been widely investigated, few studies have quantitatively examined the key strength parameters critical for engineering assessment, namely cohesion and internal friction angle. Accordingly, this study performed direct shear tests on natural snow with densities ranging from 300 to 400 kg·m^{-3} and artificial snow with densities ranging from 450 to 650 kg·m^{-3}.

Comment R2.4 (Overall):

The novelty of this paper is not that it explores compacted snow. This study still has value in terms of contributing quantifiable results that could support (or not support) conclusions made by related studies. The results of this study could also be used in the future for establishing thresholds for certain snow parameters for engineering applications. The value is more practical than novel, which is fine.

Response: Thanks!

Comment R2.5 (Overall):

Neural network and prediction modeling: The agreement between the measured data and the modeled data from the neural network looks a little too good. The level of validation is sky high. I'm wondering if the model is overfit, considering 80% of the empirical dataset was used for calibration. Also, I'm not a neural network expert by any means, but isn't this a ton of computation power for predicting only four variables? I still think having a prediction model for these parameters is very valuable, but this looks like over-fitting to me.

Response： These questions will be addressed from the following perspectives:

(1) 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.

(2) 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.

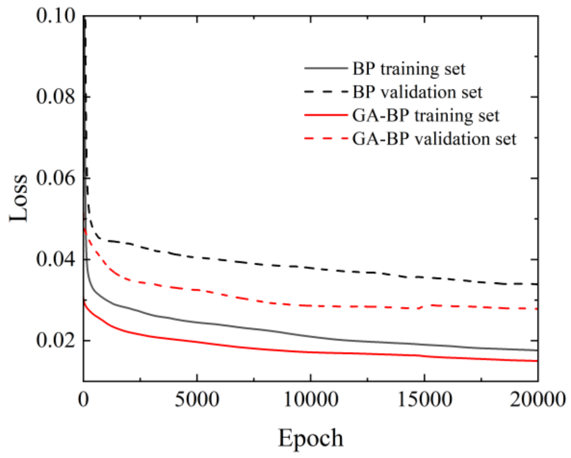


Figure 1: Epoch-loss curve

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.

Revised:

(1) Lines 288 to 295:

4 Prediction Using *GA-BP* Neural Network

As demonstrated in Chapter 3, the effects of various influencing factors on shear strength are characterized by complex interactions and nonlinear relationships. Such behaviors are difficult to characterize accurately using conventional function-fitting methods. By comparison, neural networks exhibit superior capability in processing nonlinear data. To quantitatively identify 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.

....

(2) Lines 297 to 299:

4.1.1 Data Collection and Preprocessing

A total of 448 experimental data points were obtained, among which 70% were randomly assigned to the training set, 15% to the validation set, and the remaining 15% to the test set**.......**

....

(3) Lines 344to 347

4.2.2 Neural Network Prediction Results

Upon completion of neural network training, 15% of the total dataset (67 samples), excluded from the training process, was randomly assigned as the test set. The predictive accuracy of the trained neural network was subsequently assessed by comparing the model-predicted values with the experimental measured data**.......**

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.

Comment R2.6 (Overall):

Discussion Section: This section needs a lot of work and major revision and improvements. It seems like the authors ran out of steam by the time they got to this part of the manuscript. Discussions are often the most difficult section to craft, yet the most important part of most papers. Organizing this section by snow parameter seems like a good way to start, but there are actually zero conclusions drawn from the results of the study. Each parameter listed in this section is accompanied only by some literature citations. The authors need to clearly communicate conclusions drawn from conducting the experiment, supported by the study outcomes. The overall messages that the authors wish for the readers to take away need to be stated, using specific examples from the results section as evidence for conclusions drawn. Refer to the results presented, including the empirical measurements, results from calculations, figures etc., and the modeled output. The conclusion also needs more work and should be tied back into how this study is valuable for snow structural engineering.

Response: The discussion and conclusion sections have been rewritten.

Revised:

Revised: Discussion (Lines399 to 451):

4.3 Discussion

4.3.1 Physical mechanisms governing the evolution of direct shear strength parameters

Initial density is the dominant factor governing the direct shear strength and mechanical strength parameters of compacted snow. An increase in density creates more interparticle contact points per unit volume and yields a denser internal microstructure (Butkovich, 1958; Mellor, 1977), which strengthens intergranular bonding and frictional interlocking. As illustrated in Fig. 11, both cohesion and internal friction angle rise markedly as the initial density increases from 300 to 650 kg·m^{-3}. Under a sintering temperature of -10 °C and a sintering duration of 5 days, cohesion increases from 25.73 to 161.85 kPa, while the internal friction angle grows from 18.65° to 60.98°.

The shear strength evolution of compacted snow with sintering time is governed by the coupled effects of sublimation and the formation of interparticle hydrogen bonds during sintering. In the early sintering stage, hydrogen bonds form rapidly between snow grains, whereas the density attenuation induced by sublimation remains insignificant, resulting in a rapid rise in shear strength. Subsequently, the sintering process gradually stabilizes, accompanied by sustained density reduction. Controlled by the interplay of these two mechanisms, the shear strength fluctuates slightly and maintains a relatively stable level. As sintering time further prolongs, sublimation gradually dominates the structural evolution, leading to a continuous decline in shear strength.

During sintering, the protrusions on snow grain surfaces undergo preferential sublimation, rendering particle morphologies more regular (Bahaloo et al., 2024; Colbeck, 1983a; Paterson, 1994; Wang, 1982; Zhuang, 2019). This smoothens particle surface roughness and consequently induces a gradual reduction in the internal friction angle. By contrast, cohesion exhibits a variation trend consistent with that of shear strength, rising initially and then declining slowly. Taking the specimen with a density of 550 kg·m^{-3} sintered at -10 °C as an example (Fig. 14), as sintering time extends to 60 days, cohesion first increases from 53.54 to 141.85 kPa and then decreases to 131.99 kPa; meanwhile, the internal friction angle drops from 52.78° to 38.58°.

Elevated sintering temperature intensifies the Brownian motion of water vapor, which promotes the formation of hydrogen bonds among snow particles (Abele, 1967, 1990;

Colbeck, 1983a). A higher sintering degree further reinforces interparticle bonding and regularizes grain surface morphology. As shown in Fig. 15, when the sintering temperature rises from -25 to -5 °C, cohesion increases considerably. For specimens with a density of 550 kg·m^{-3} sintered for 15 days, cohesion increases from 115.4 to 183.72 kPa, while the internal friction angle decreases from 48.69° to 41.74°.

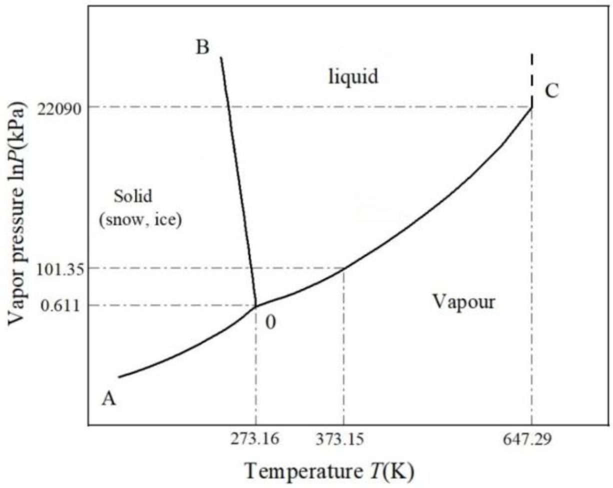


Figure 24: Phase diagram of water (A denotes the sublimation line, B denotes the melting line, and C denotes the evaporation line).

4.3.2 Comparison with existing studies

This study systematically investigated the variation patterns of shear strength and its key parameters of compacted snow, with a focus on the effects of three critical factors: initial density, sintering time, and sintering temperature. The influences of initial density and sintering temperature observed in this study are consistent with the findings of previous research (Butkovich, 1958; Ballard et al., 1965; Perla & Beck, 1982; Schweizer, 1998). With respect to the effect of sintering time, similar conclusions have been corroborated by both field investigations and laboratory experiments (Jellinek, 1959; Zhuang, 2019; Fu, 2020; Yang, 2024).

In contrast, Abele (1990) reported that the sintering strength of snow continued to increase without exhibiting a decreasing trend. However, the experimental details (e.g., ambient humidity and specimen sealing conditions) were not clearly described in that study, which may have led to discrepancies in the observed results. Therefore, more refined and controlled experiments are required in future research to further clarify and verify the strength variation patterns of compacted snow.

4.3.3 Highlights and limitations of this study

Combining laboratory experiments and a neural network model, this study established baseline direct shear strength parameters for compacted snow covering a range of influencing conditions: an initial density of 300 to 650 kg·m^{-3}, sintering temperature of -25 to -5 °C, sintering duration of 0 to 60 days, and normal stress of 25 to 100 kPa. The derived baseline parameters can provide a reference for engineers to conduct deformation analysis, bearing capacity evaluation, and stability calculation of snow-based infrastructures in polar and cold regions. When snow type or environmental conditions vary, updated strength parameters can be acquired via laboratory testing. By further establishing the quantitative correlation between newly measured parameters and the baseline values proposed in this study, targeted correction of the existing baseline data can be realized.

This study solely considered four influencing factors, namely initial density, sintering temperature, sintering time, and normal stress within the range of 25 to 100 kPa, with a fixed shear loading rate of 0.8 mm·min^{-1}. The evolution characteristics of the shear strength parameters of compacted snow under additional internal and external influencing factors remain to be explored in future research. Key internal factors include snow type, liquid water content, and particle size distribution, while major external factors cover ambient humidity, specimen sealing conditions, loading rate, and extended normal stress levels.

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.

……

(2) Conclusions (Lines 470 to 475):

5 Conclusions

……

(4) Based on the (GA-BP) neural network, this study establishes benchmark values of shear strength parameters for compacted snow under different initial densities, sintering durations, and sintering temperatures. These benchmark values provide reliable quantitative references for the design, construction, and performance optimization of

snow-based structures in engineering practice. In future research, the proposed benchmark values can be adapted and extended to accommodate diverse engineering environments and compaction technologies, thereby supporting the rational selection of parameters and comprehensive performance evaluation of snow engineering structures across various application scenarios.

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 Lines-number comments

L30: Deeper snow layers, especially at the base of the snowpack, do not always get stronger over time from compaction of overlying snow layers. Changes in the temperature gradient from top to bottom of the snow profile often cause faceting and weakening of the basal layer crystal bonds. Qualify this sentence by specifying under what conditions at a snow construction site would base layers of the snowpack be strongly bonded and not faceted.

Response: Thank you for your comment. The author has removed the inaccurate statements from the original manuscript and revised the sentences.

Revised: Lines 29 to 30:

In engineering applications, snow is usually compacted and sintered to enhance the strength of snow layers (Sun et al., 2021).

L35: which snow layer? Or referring to snow in general?

Response: This refers generally to snow; the manuscript has already been revised.

Revised: Lines 32 to 34:

Additionally, lower temperatures slow down the sintering process (Abele, 1990); consequently, the temperature of the snow ~~layer~~ is often raised to accelerate sintering and rapidly attain the target engineering strength (White, 2023).

L46: awkward wording, "shear rate strongly influences snow strength and failure modes...."

Response: Thanks. Revisions have been made.

Revised: Line 45:

Shear rate strongly influences snow strength and failure modes.

L47: awkward wording, do you mean "strength initially increases, then subsequently decreases rapidly with the transition from ductile to brittle"?

Response: Thanks. Revisions have been made.

Revised: Lines 45 to 47:

Shear strength initially increases, then subsequently decreases rapidly with the transition from ductile to brittle (McClung, 1977; De Montmollin, 1982; Puzrin et al., 2019).

L50: I think I understand the concept here, but the sentence needs rewording for clarity

Response: Thanks. Revisions have been made.

Revised: Lines 47 to 49:

De Montmollin (1982) examined the effect of shear rate on snow failure and categorized the failure modes, showing that in the medium-to-high shear rate regime, both shear strength and residual stress after brittle failure decrease with increasing shear rate.

L56: Name the three instruments described and invented in 2016, 2010, and 2013.

Response: All three instruments were developed independently by the researchers, and their names are not mentioned in the original literature. The author has provided additional notes in the manuscript describing the operating conditions of these three instruments to clarify their functions.

Revised: Lines 54 to 61:

To address this limitation, Barbero (2016) developed an in-situ direct shear testing apparatus that integrates sampling and shearing functions, enabling the retrieval of nearly undisturbed snow specimens and allowing accurate control and monitoring of normal and shear stresses via a pneumatic system. Reiweger (2010) designed a laboratory loading device capable of tilting snow samples to simulate actual slope angles; this device applies incremental weights to replicate snow overburden loading and can be coupled with particle image velocimetry for local strain analysis and acoustic emission monitoring to trace damage evolution. Podolskiy (2013) developed a portable shear loading apparatus that enables shearing along a predefined weak interface; by sintering two snow blocks and shearing at the bonded interface, the apparatus can be adopted to quantify the contribution of sintering to snow shear strength.

L61: What is a "variation pattern"? This seems vague to me. Are you referring to snow strength spatial variability across a landscape? Or snow strength variations temporally over a winter season or variations in the snowpack profile?

Response: The authors intended to convey in the original text that the trends in snow intensity vary with different influencing factors. This section has been revised in the manuscript.

Revised: Lines 64 to 66:

Although the shear strength of snow has been widely investigated, few studies have quantitatively examined the key strength parameters critical for engineering assessment, namely cohesion and internal friction angle.

L65- 69: The specific study objectives need to be clarified here.

Response: Revisions have been made.

Revised: Lines 67 to 75:

A total of 112 test conditions were designed considering the coupled effects of initial density, sintering time, and sintering temperature, and systematic direct shear tests were carried out on compacted snow specimens. Based on the shear stress–displacement curves, shear strength was defined as the peak shear stress for strain-softening responses and as the shear stress at a shear displacement of 4 mm for strain-hardening responses. The cohesion c and internal friction angle φ were then determined in accordance with the Mohr–Coulomb linear criterion, and their magnitudes and variation characteristics under different influencing factors were analyzed. A Genetic Algorithm-Back Propagation (GA-BP) neural network was employed to establish a predictive model for shear strength parameters under multi-factor coupling conditions, thereby providing benchmark values for c and φ under various combinations of influencing factors.

L75- 84: Clarify which of these steps described in the methods are for the initial snow making process and which are the subsequent sample collection and preparation steps.

Response: The title of Section 2.1 has been changed to *Snow Production and Sample Preparation*

L80: Where was this done? In a cold lab?

Response: The snowmaking process takes place outdoors, while the remaining steps (sample preparation, sintering, and shearing) are all performed in a temperature-controlled freezer. The manuscript has been revised.

Revised:

Lines 88 to 89: The environmental parameters for outdoor snow production were controlled as follows: temperature of -5 °C, relative humidity of 30 %, wind speed of 6 to 7 m·s^{-1} , snowmaking machine elevation angle of 45°, and spraying distance of 10 m.

Line 105: all compaction procedures were performed in a -10 °C cold chamber

L82: the snow crystals were plate- like, not the snow samples

Response: Thanks. Revisions have been made.

Revised: Lines 93 to 94:

Following the classification by Barrett et al. (2012), the snow crystals were plate-like, with particle sizes ranging approximately from 0.5 to 1.5 mm.

L89: were the uniform snowflakes spread inside the ring before sealing with the membrane? It sounds like the opposite, i.e. the snowflakes were added after applying the membrane.

Response: When a snow specimen is exposed to the external environment, the surface in contact with the air sublimates rapidly. In practical engineering, the snow we test is inside the snow layer and does not directly contact the air. This experiment simulated real conditions: during sintering, the ring mold was completely surrounded by snow, but the upper and lower surfaces of the specimen were also covered with snow, which easily led to hydrogen bonding and cementation between the specimen surface and the external snow. When preparing for the shear test, the specimen had to be separated from the surrounding snow, which inevitably disturbed the specimen. Therefore, a thin film was applied to the specimen to solve this problem. During sintering, gas exchange between the specimen and the environment remained possible, but cementation with external snow was prevented.

Based on the above response, the authors revise and supplement the original content of the manuscript.

Revised: Lines 107 to 115:

Sintering: to simulate the natural sintering environment, a sealing membrane was placed over the compacted specimen while it remained inside the ring formwork. Uniform snowflakes were then distributed around the specimen and across the membrane to replicate the in-situ conditions within a natural snowpack. The surrounding snowflakes mitigated rapid sublimation from exposed surfaces, whereas the membrane isolated the specimen from the overlying snow, thus preventing unintended sintering bonding between the specimen and external snow. The entire assembly was subsequently placed in a temperature-controlled test chamber and sintered at the prescribed temperature for the designated duration. Specimens covered with sealing membranes are shown in Fig. 1(b), and snowflakes deposited on the specimens and membranes are presented in Fig. 1(c).

(a) (b) (c)

Figure 1: Sample preparation process ((a) Compacted specimen; (b) Samples covered with membranes; (c) Sprinkling snowflakes).

L96: I think you mean "snow sample shearing process, using the equipment", not "equipment shearing process".

Response: Thanks. Revisions have been made.

Revised: Line 123: The shearing process of the snow specimen is illustrated in Fig. 3

L100: This is confusing. How would one pre- define the shearing plane? The samples will shear where the two boxes meet, correct?

Response: In the direct shear tests conducted in this study, the shear plane was created by the horizontal displacement between the upper and lower shear blocks. The original sentence was intended to emphasize that no artificial weak planes were introduced during specimen preparation. To avoid ambiguity, the manuscript has been revised.

Revised: Lines 126 to 129:

A dynamometer is installed on the upper shear box. The shear plane is determined by the interface between the upper and lower shear boxes; no artificial weak plane is prefabricated in the specimen, and shear failure occurs naturally as the lower box moves horizontally relative to the upper box.

2.2 and 2.3: Be more consistent and accurate when referring to shear force (force per unit area) vs. shear rate (displacement over time). Also be consistent and clear on the difference between the applied shear stress vs. how this study reasonably decided to define shear strength (amount of applied stress required for plastic deformation, or measured shear stress at 4mm displacement when plastic deformation does not occur).

Response: Thanks. The usage of "shear stress" and "shear strength" has been standardized throughout the manuscript.

Fgure 4: The x- axis label needs to include the units. 图 4：x 轴标签需要包含单位。

Response: Thank you for pointing that out. The original image has been corrected.

Revised:

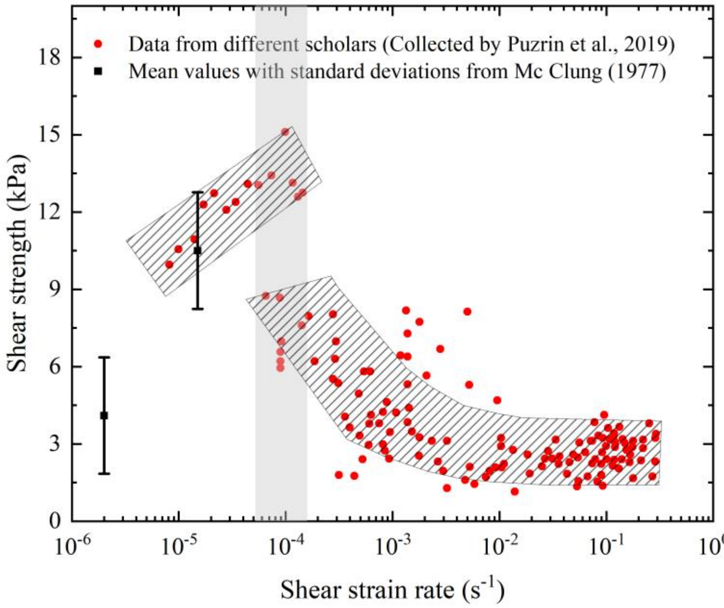


Figure 5: Variation of shear strength with shear strain rate (Redrawing from Puzrin et al., (2019))

L106- 108: This sentence is very confusing. What is increasing initially and then shows a decreasing trend? Strength or strain? Also the relationship here is stated as shear strain rate vs. strength, but the axes in figure 4 are labeled as strain rate vs. stress. Be consistent.

Response: Thank you for your comment. The author has revised the sentence in the original text to avoid any ambiguity. Additionally, the vertical axis label in Figure 4 has been confirmed as *Shear strength*, and the horizontal axis label is *Shear strain rate*.

Revised: Lines 132 to 134:

Fig. 4 (redrawn from Puzrin et al., 2019) shows that the shear strength of snow first increases and then decreases with increasing shear strain rate, and the shear strength parameters also vary accordingly.

L115: Clarify what is meant by "patterns in failure modes and strength variations".

Response: Thank you for your comment. *Failure* refers to the two types of shear stress-displacement curves (strain hardening and strain softening); *strength variation* refers to changes in the snow's shear strength in response to external factors. To avoid ambiguity, we have revised the manuscript as follows.

Revised: Lines 141 to 142:

Moreover, the transition between these two failure modes exhibited a clear trend, and the variation in shear strength with external factors followed a similarly well-defined pattern..

L127: Is this really data processing or data collection?

Response: In the manuscript, *Data Processing* has been changed to *Data Collection and Processing*.

L135: provide a citation for the 400kg/m³ threshold or where does this quantity come from? This sentence also needs to be written more clearly. What is meant by interparticle friction impeding density? Do you mean that 700kg/m³ is as dense as snow can get before turning to glacier ice or firn? Refer to Cuffey and Patterson, 2010, for density ranges for snow, firn, and ice.

Response: Thank you for your comment. Regarding the source of the density threshold between 400 and 700 $kg \cdot m^{-3}$ and the expression "interparticle friction hinders density increase", we provide the following clarification and revision.

(1) Source of the 400 $kg \cdot m^{-3}$ threshold:

This threshold is mainly based on pre-test observations in this study. For artificial snow, when the density is below 400 $kg \cdot m^{-3}$, the internal structure of the specimen is loose and the pores are large. It is difficult to form an intact and stable specimen. When the density reaches 450 $kg \cdot m^{-3}$, the specimen already exhibits good formability after compaction and can meet the requirements for subsequent sintering and shear tests. Therefore, this study selected 450 kg·m⁻³ as the lower limit of density for artificial snow.

(2) Regarding the 700 kg·m⁻³ threshold and the expression "interparticle friction":

The original expression "interparticle friction hinders density increase" was not sufficiently accurate. What we intended to convey is that during mechanical compaction, when the density approaches 700 kg·m⁻³, the contact area between snow particles increases significantly, and the interparticle frictional resistance rises sharply. This makes further compaction extremely difficult. Under the laboratory conditions of this study, 650 kg·m⁻³ is the maximum density that can be achieved by manual compaction using tools. In nature, this density range corresponds to the transition from firn to ice (Cuffey & Paterson, 2010). Therefore, this study selected a density range of 450–650 kg·m⁻³.

We have revised the wording in the main text accordingly, and added a description of natural snow specimens with densities ranging from 300 to 400 kg·m⁻³.

Revised: Lines 177 to 187:

Naturally deposited snow must be compacted before being used as an engineering material. Preliminary tests indicated that for machine-made snow with an initial density of approximately 300 kg·m⁻³, specimens remained loose with large internal pores and could not maintain structural stability when compacted to a density below 400 kg·m⁻³. When the compacted density reached 450 kg·m⁻³, the specimens exhibited satisfactory formability and integrity after compaction, satisfying the requirements for subsequent sintering and shear tests. Under mechanical compaction, the interparticle contact area increases significantly as the density approaches approximately 700 kg·m⁻³, resulting in a rapid increase in frictional resistance that makes further densification extremely difficult. Under the laboratory conditions of this study, the maximum density achievable via manual compaction was 650 kg·m⁻³. Similarly, for natural snow with an initial density of approximately 200 kg·m⁻³, stable specimens could only be formed when compacted to 300 kg·m⁻³. Therefore, natural snow was used to prepare specimens with densities ranging from 300 to 400 kg·m⁻³, and machine-made snow was used to prepare specimens with densities ranging from 450 to 650 kg·m⁻³.

Table 1: The Serial # column could use a description of why the various experiment trials were labeled D- 1 vs t- 1 vs T- 1, etc. It's somewhat obvious, but only after reading well past the table and then referring back to it. The way multiple trials are listed on one Lines totally makes sense and is easy to understand, but I don't get the numbering in the first column, i.e., the first Lines (D- 1) is really tests 1 through 20, and the second Lines (D- 2) is for tests 21 through 40; the fourth Lines is for tests 61- 72, I think. Lastly, it was stated earlier that there were 69 test conditions, but this table shows many more parameter combinations and tests than that.

Response: Table 1 has been revised and updated with new operating conditions, and a note has been added to clarify that each operating condition consists of four normal stresses, in order to avoid ambiguity.

Revised: Lines 188 to 190:

The effects of initial density ρ, sintering time t, and sintering temperature T_s were systematically examined through 112 test conditions, as detailed in Table 1. Each test condition incorporated shear strength measurements at four normal stress levels, resulting in 448 sets of valid shear strength data points.

Table 1 Test conditions.

Serial number	ρ（$kg \cdot m^{-3}$）	t（days）	T_s（°C）	Other variables
D-1	300,350,400,450,500,550,600,650	5	-5	σ=25,50,75,100 kPa
D-2	300,350,400,450,500,550,600,650	5	-10	σ=25,50,75,100 kPa
D-3	300,350,400,450,500,550,600,650	5	-20	σ=25,50,75,100 kPa
t-1	300	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-2	350	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-3	400	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-4	450	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-5	550	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa
t-6	650	0,1,3,5,10,15,20,30,60	-10	σ=25,50,75,100 kPa

T-1	300	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-2	350	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-3	400	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-4	450	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-5	550	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
T-6	650	15	-5, -10, -15, -20, -25	σ=25,50,75,100 kPa
H-1	300	1,30	-5, -20	σ=25,50,75,100 kPa
H-2	350	1,30	-5, -20	σ=25,50,75,100 kPa
H-3	400	1,30	-5, -20	σ=25,50,75,100 kPa
H-4	550	1,30	-5, -20	σ=25,50,75,100 kPa

L144-145: This needs to be stated at the beginning of the paper, i.e. "In our study, we define shear strength as the peak shear stress right before plastic deformation or critical displacement", or a similar statement should be in the introduction and/or methods sections.

Response: The relevant content has been added to the introduction of the manuscript.

Revised: Lines 69 to 71:

Based on the shear stress–displacement curves, shear strength was defined as the peak shear stress for strain-softening responses and as the shear stress at a shear displacement of 4 mm for strain-hardening responses.

Figure 7: The idea of representing the shear stress - displacement curves in this alternative way seems creative and intuitive to me. I really like this figure. However, I wondering if I don't understand how to read it correctly. Maybe a sentence or two in the text on how to read this figure would help. Because I thought I got it, but to me, it looks like in graph (a), at 25kpa normal force, density of 650kg/m^3, t = 5 days, Temp = -10 deg C, the peak shear displacement is roughly 2mm, but in graph (b) the same combination of parameters shows the peak shear displacement as more like 3mm.

Response： Thank you for your comment! The color scheme in the original figure was indeed inconsistent, so Figure 7 has been redrawn.

Revised:

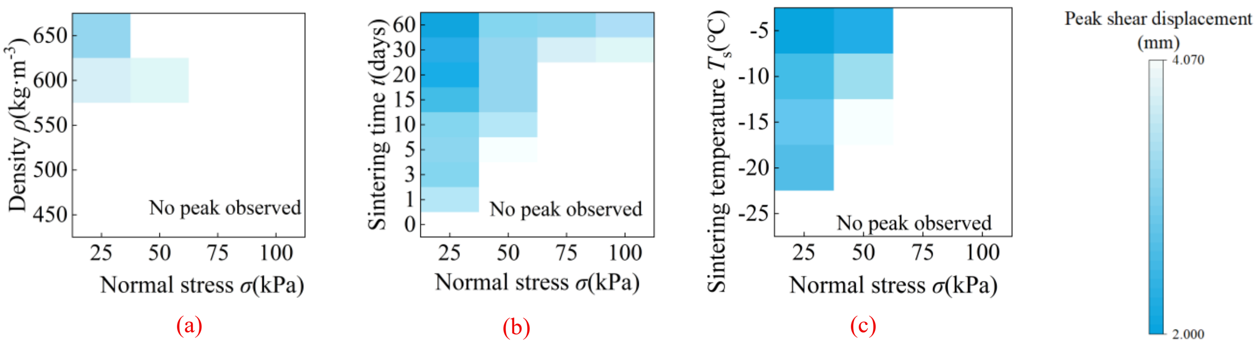


Figure 8: Development trends of shear stress–displacement curves under varying influencing factors ((a) Different densities; (b) Different sintering times; (c) Different sintering temperatures).

Equation (1) and the process of calculating internal friction angle and cohesion needs to be added in the methods section. One or two sentences in the methods should be fine.

L173: Which author are you referring to here? At first I thought this was in reference to the authors of the citations provided for equation (1), but then it says the "advance shear tests up to 350kpa" were done in the experiments from this paper? This is a whole new aspect/component of the experiment not described previously in the methods section. This needs to be added as the first step, or one of the first steps, in the methods.

Response: Thank you for your comment. The two issues mentioned above have been addressed in the manuscript. We have added the calculation procedures for cohesion and internal friction angle to the experimental methods section, as well as the preliminary tests.

Revised: Lines 166 to 174:

Many previous studies (McClung, 1977; Barbero, 2016; Perla, 1977; Fyffe, 2007; Chiaia, 2008; Gaume, 2014) have adopted the Mohr–Coulomb criterion as the failure criterion for snow. Preliminary tests were first conducted under normal stresses ranging from 25 to 350 kPa to determine the linear portion of the shear strength–normal stress envelope. Based on the test results, the mean values and standard deviations of shear strength for the three parallel specimens under each condition were plotted. According to the linear Mohr–Coulomb criterion (Eq. 2), the cohesion *c* and internal friction angle

φ were determined using the least squares method, and the error bars of c and φ were plotted based on the fitting results.

$$\tau_f = c + \sigma \tan\varphi \quad (2)$$

where τ_f is the shear strength, σ is the normal stress, and c and φ denote cohesion and internal friction angle, respectively.

L174: what is a "partial test"?

Response: This refers to preliminary experiments conducted under normal stresses ranging from 25 to 350 kPa; the manuscript has been revised to avoid any misleading statements.

Revised: Lines 223 to 224:

Fig. 9 presents the shear strength envelopes of compacted snow under different normal stresses, obtained from ~~partial~~ tests.

Section 3.2.2: I enjoyed looking at the data and results in this section, but there is nothing that new here. It more or less just shows how snow crystal sintering over time increases bonding up to a certain point, but with continued aging of the snowpack, there is mass loss and bond weakening due to sublimation. This can be seen in the experiment's laboratory generated snowpack, as evidenced by the graphs in this section. Also, shows evidence to support that warmer temperatures lead to stronger bonding, which is well known. I suggest moving this section into an appendix. It's neat to look at but makes the paper longer than necessary.

Response: Thank you for your comment. We have revised the content in Section 3.2.2 and moved some of it to the discussion section.

L249: define "back propagation".

Response: The definition of the BP neural network has been added in 4.1.2 *BP Neural Network Model*.

Revised: Lines 305 to 306:

A back-propagation (BP) neural network updates connection weights through error back-propagation from the output layer to the input layer, and is commonly utilized for nonlinear function fitting and approximation

In addition, Section 4.1.3, *GA-BP Neural Network Model*, provides a detailed description of the specific construction method for the GA-BP neural network.

Section 4.1 belongs in the methods.

Response: Revised to ***4.1 Model Establishment Method***

L255: Where did the 276 points come from? This is the first its mentioned in the paper and might be the number of tests in Table 1? How do these relate to the 69 test conditions?

Response: Thank you for your comment. We have added additional notes regarding the operating conditions in Table 1.

Revised: Lines 188 to 190

The effects of initial density ρ, sintering time t, and sintering temperature T_s were systematically examined through 112 test conditions, as detailed in Table 1. Each test condition incorporated shear strength measurements at four normal stress levels, resulting in 448 sets of valid shear strength data points.

Section 4.1.3 needs to be much expanded. This whole component of the study, the neural network, is not explained in any detail.

Response: It has been expanded to explain the specific steps involved in neural network models.

Revised: Lines 320 to 329:

4.1.3 *GA-BP* Neural Network Model

To mitigate the risk of local optima caused by random initialization, a genetic algorithm (GA) was employed to optimize the initial weights and thresholds of the BP neural network. A population of real-valued individuals encoding candidate weights and biases was randomly generated, and the fitness function was defined as the reciprocal of the mean squared error between the predicted and measured shear strength values. Through selection, crossover, and mutation operations, the population evolved iteratively until the predefined termination criterion was satisfied. The optimal individual obtained was then used to initialize the BP network, which was further trained by forward propagation and error backpropagation until convergence. The established GA-BP model was adopted to predict the shear strength corresponding to given inputs of density, sintering time, sintering temperature, and normal stress. The complete flowchart and key parameters of the GA are presented in Fig. 18 and Table 2, respectively.

Figure 18 is very good.

Response: Thanks.

Figure 19: Do the serial numbers on these x- axes relate to Table 1 somehow? The way the trials/tests are numbered needs improvement and more consistency throughout the paper.

Response: Thank you for your comment. The numbers on the x-axis in Figure 19 represent the test results for a test set comprising 15% (67 groups) of all shear strength values (448 groups) selected at random; these numbers are unrelated to the item numbers in Table 1. We have added a clarification to the original text to avoid any ambiguity.

Revised: Lines 345 to 347:

Upon completion of neural network training, 15% of the total dataset (67 samples), excluded from the training process, was randomly assigned as the test set. The predictive accuracy of the trained neural network was subsequently assessed by comparing the model-predicted values with the experimental measured data.

Figure 19(a): The agreement between the measured data and the modeled data from the neural network looks a little too good. The level of validation is sky high. I'm wondering if the model is overfit, considering 80% of the empirical dataset was used for calibration.

Also, I'm not a neural network expert by any means, but isn't this a ton of computation for predicting only four variables?

Response: The question regarding neural networks has already been responded in Comment R2.5 (Overall).

L289: What is the "Connection Weights Method"? I don't see this mentioned anywhere else in the study.

Response: An explanation of the connection weight method has been added to the manuscript.

Revised: Lines 338 to 340:

Fig. 19(b) illustrates the relative importance of each input variable to shear strength, calculated using the Connection Weights Method (Olden et al., 2004), which quantifies variable importance by means of the raw connection weights between adjacent network layers.

References:

Olden, J.D.; Joy, M.K.; Death, R.G. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. Ecol. Model., 178, 389–397, https://doi.org/10.1016/j.ecolmodel.2004.03.013, 2004