Tensile Experiments on Adhesion between Aluminium Profiles and Glass*

Svein Olav Nyberg[1(✉)], Kjell G. Robbersmyr[1], Jan Andreas Holm[1], and Filippo Sanfilippo[1]

Dept. of Engineering Sciences, University of Agder (UiA)
Jon Lilletuns vei 9, NO-4879, Grimstad, Norway
sveinon@uia.no

Abstract. In this work, the effects of the adhesion between aluminium profiles and glass are studied from a static tensile perspective. A series of stretch curves are analysed from their derivatives to find their points of float and maximum load bearing. The variable factors are glass type, and type of connection: i.e., edge adhesive, side (fugue) adhesive, and excessive fugue adhesive, for short named *fugue-edge*. The stretch data imply four quantities to analyse and compare: displacement and load respectively at float and at max load. The results are first compared factor group against factor group. With this tool, only a few significant conclusions may be found. The second comparison is by means of the more robust statistical tools of linear regression and analysis of variance (ANOVA), with conclusions about which factors are significant, and then about the size of the effect on the four variables under study. This forms the basis for a recommendations for how to obtain the strongest possible glass-frame system.

Keywords: Adhesion · Aluminium profiles · Glass · Linear regression · Analysis of variance.

1 Introduction

Over the last few decades, the usage of structural adhesives in civil engineering and in the manufacturing industry has risen substantially [8]. While bonded joints have considerable benefits over traditional connections, their behaviour must be predicted taking into consideration various factors such as environmental exposure during application and service life, and adherent type. The primary issue with the mechanical performance of the metal-glass connection is the brittleness of the glass, which makes designing structural components with cooperating glass problematic. Because of this property of glass, conventional connections (such as bolted joints) are not appropriate. When compared to conventional joints, bonded joints offer a viable option since they allow consistent stress distribution, minimise stress concentration, and reduce junction weight.

* This research is funded by the Top Research Centre Mechatronics (TRCM), University of Agder (UiA), Norway.

However, it is challenging to assess their nonlinear mechanical behaviour and mechanical performance under various environmental exposure circumstances.

Recent advances in the research of structural adhesives [1,5,7,9] have shown that by connecting together brittle and ductile materials (for example, glass and steel, respectively), the mechanical behaviour of the glass structure may be improved. This combination allows for the creation of a very ductile structure with high gloss and clarity. Overend et al. [10] conducted mechanical and computational modeling experiments to investigate the performance of five adhesives for load-bearing steel-glass connectors. Mechanical testing on steel-glass connections gave valuable information for choosing an adhesive (silicone).

By following these research trends, the results of an experimental campaign on glass-aluminum bonded joints are presented in this article.

The paper is organised as it follows. A review of the related research work is given in Section 2. The conducted experiments are described in Section 3. In Section 4, the proposed methodology is presented along with the results of the analysis. Finally, conclusions and future works are discussed in Section 5.

2 Related Research Work

The broad demand for lightweight, robust, and long-lasting materials in industrial applications has provided a significant push for research and development. In order to meet these criteria, it may be essential to combine elements that appear to be incompatible [2]. As a result, innovative technology processes capable of efficiently combining different materials (i.e., hybrid joint) are in great demand in the industrial sector.

Several related studies exists in the literature. For example, the durability of glass/steel bonded junctions subjected to adverse conditions was investigated in [2]. Pull-off mechanical tests were performed in this context in order to evaluate the performances evolution and damage phenomena of the bonded joints during the ageing exposition. The performance of two different adhesives were compared (i.e., epoxy and polyurethane ones). The impacts of the glass surface condition and the presence of a basalt mat layer inside the adhesive thickness were also considered. The mechanical performances were linked to the failure mechanisms that occurred. In [6], experiments were carried out to understand and anticipate the behaviour of dissimilar bonded junctions under quasi-static and impact stresses, employing composite and aluminium substrates. Following the requirements for the automobile sector, a variety of testing temperatures were examined. It was fair to assert that, when used in combination with modern crash resistant adhesives, different bonded joints can effectively be used for the construction of automotive structures, with good energy absorption capabilities under impact and no significant sacrifices in joint performance. In [11] the strength properties of aluminium/glass-fiber-reinforced laminate with an additional epoxy adhesive film inter-layer were considered. The interesting aspect of this former study is that the application of the adhesive film as an additional binding agent caused an increase in laminate elasticity. In [4], the effect of surface roughness for improving interfacial adhesion in hybrid materials with aluminium/carbon fiber reinforced epoxy composites was investigated. Various types of sanding paper and varying sanding sessions were used to regulate the roughness of the aluminium's surface. After various sanding procedures, the surface roughness of aluminium was measured using static contact angle (CA) and 3D surface scanning. The interfacial adhesion between the various alluminium surface treatments was evaluated using lap shear strength (LSS) tests. Surface treatment of aluminum in these materials has great potential for improving mechanical characteristics in aerospace, automotive, and other practical applications.

There is still a need for more accurate static tensile experiments on adhesion between aluminium profiles and glass, especially considering that, during their service life, the joining elements are exposed to various factors (e.g., ultraviolet (UV), temperature, moisture) that may affect their mechanical performance.

3 Experiments

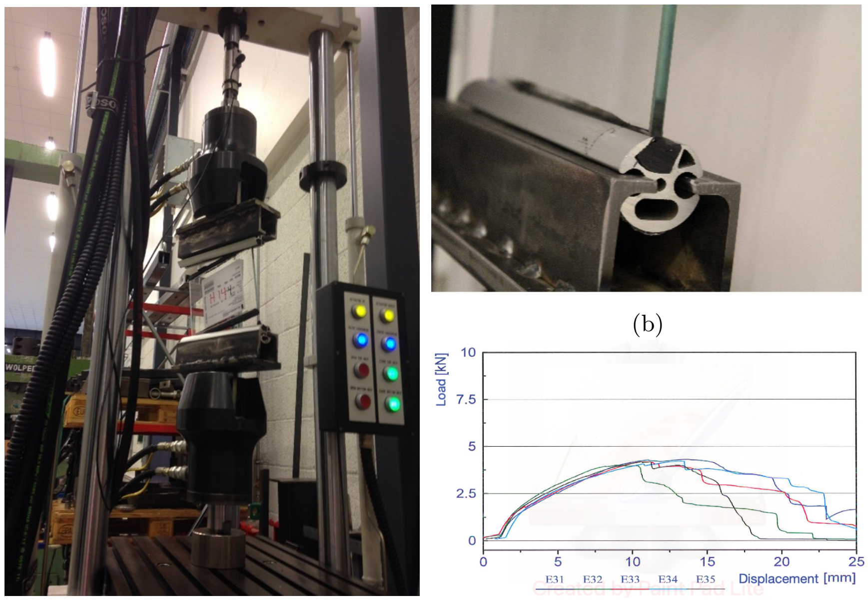
The main objective is twofold: to test the adhesion between the glass and the adhesive, and between the aluminium profile and the adhesive.

3.1 Materials

The aluminium profile, made of ETC 5129 (anodised), has the shape as shown in Figure 1b. The figure also shows the joint or the connection between the profile, the adhesive and the glass. The dimensions of the glass/polycarbonate are as follows: width = 200 mm, height = 150 mm and the thickness = 6,0 mm (glass) and 5,0 mm (polycarbonate). Three factors of adhesive, and two types of glass with different types of processing of preparation were tested in combinations, as shown in Table 1. The number of samples in each group is 5, with the exception of two of these groups, which have 4.

3.2 Static Tensile Properties

The tests were performed as pure static tensile tests. A suitable test setup was developed including two fixtures to attach the test samples to the tensile testing machine. The adhesive was applied to the surfaces prescribed for each sample type in a uniform manner by the same operator. The tensile testing machine has the following designation: servo-hydraulic benchtop test machine type 804H. Figure 1a shows the clamping of the test sample in the tensile testing machine. The tests were performed by stretching the sample to fracture at a stretching speed equal of 0.02 mm/s until the frame had lost grip on the glass. The total time naturally differed between the tests. The applied load and the extension are logged, yielding the stretch curves shown in Figure 1c.



(a) (b) (c)

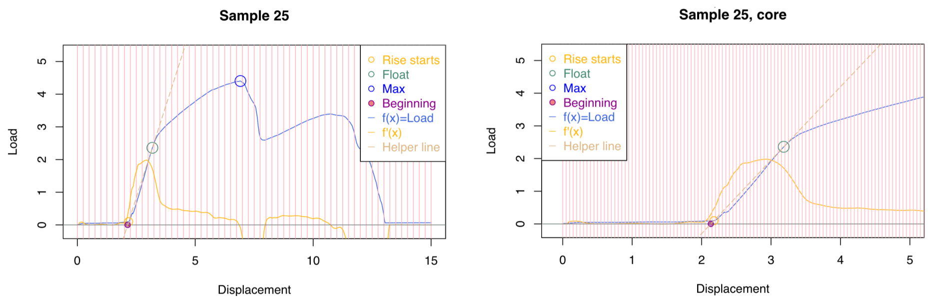
Fig. 1: Experiment illustrations: (a) machine set-up; (b) mounting profile; (c) load vs displacement curves.

4 Methodology and Results

The analysis of the load test data goes in two steps, the first of which is to extract the key points from the detailed profile of stretch data. The second is to analyse the table of key data to look for patterns.

4.1 Extracting the Key Points

The data pairs consist of load vs displacement, and a typical profile looks like Figure 2a (close-up: Figure 2b). The main curve (blue) is the load vs the displacement, and the secondary curve (orange) is its smoothed derivative. The float point is the first key point. It is the first point after max derivative where the derivative dips below 85% of the max derivative value. Precisely 85% is somewhat arbitrary, but it gave the least amount of disturbance due to the derivative not being absolutely smooth, all the while staying reasonably close to where visual inspection indicated the curve was tapering off. The max load is simply at max load. To find the start of the process, draw a straight line through the float point and the beginning of the rise up to it, as indicated by two open circles. The smaller full circle is then the estimated starting point. Subtract this value from the displacement values.



(a) (b)

Fig. 2: Displacement-load profile: (a) individual load curve; (b) close-up.

The float point and the point of max load are the most interesting sites, as they are the keys to assessing critical strength for glass-in-metal frame constructions. As such, the float point is the point before which a reversal of forces will return the adhesive back to its original shape. Both displacement and force at these points matter to these assessments. This is important to the long-term life of a construction with glass in a metal frame, such as a car, a boat or a plane. The second points of interest is the point of maximum force; that is, the force and the displacement at this point. Though this only has a one-time applicability in for instance a crash, this one time is a rather important event to plan and therefore calculate for. A possible third point of interest is on the way down from max force where the adhesive has not totally given up the glass yet, but no unique good point which could serve this function has manifested itself.

Table 1 sums up these measurement series, loaded into R (programming language) as a dataframe named *tD*. In this analysis, the significance levels are the conventional ones, 0.1 (.) 0.05 ($*$), 0.01 ($**$) and 0.001 ($***$).

4.2 Analysis of Key Points, Take 1: Pairwise *t* Tests

Table 1 presents *four* different values to analyse: y_1 =Displacement at float point, y_2 =Load at float point, y_3 =Displacement at max load, y_4 =Max load.

The question is how the different factors, x_1 =Glass type, (B) x_2 =Edge adhesive, x_3 =Fugue adhesive, and x_4 =Extended fugue edge adhesive, influence the four values.

The simplest method calculates effect from grouped means and standard deviations. This is the *pairwise t test*.

Example: To see if x_1, Glass type, makes a significant difference to y_1, load at float point, write the following command in R:

```
t.test( tD[tD$x1==”PC”,]$y1, tD[tD$x1==”GL”,]$y1 )
```

This generates the following output:

Table 1: Raw data.

LNR	x_1=Glass	x_2=Edge	x_3=Fugue	x_4=FugueEdge	y_1=floatDisp	y_2=floatLoad	y_3=topDisp	y_4=topLoad
11	GL	1	0	0	0.913704657	1.8585	2.213804657	2.6863
12	GL	1	0	0	0.930844519	2.2858	3.491344519	3.4309
13	GL	1	0	0	0.940517524	2.3094	5.191617524	3.5782
14	GL	1	0	0	0.974659503	2.2385	4.288859503	3.4744
15	GL	1	0	0	0.83215012	1.9394	2.85085012	2.8244
21	GL	1	1	1	1.002709147	2.2316	4.500109147	3.8788
22	GL	1	1	1	1.092222408	2.5627	5.465422408	4.7325
23	GL	1	1	1	1.185509437	2.3796	4.121309437	3.9398
24	GL	1	1	1	1.046217805	2.4078	4.140617805	4.1893
25	GL	1	1	1	1.049969533	2.3598	4.782269533	4.4029
31	GL	1	1	0	0.867274823	2.1805	3.300974823	3.5172
32	GL	1	1	0	0.869963177	2.1873	5.102703177	4.0619
34	GL	1	1	0	0.80657587	2.0172	4.46102587	3.2227
35	GL	1	1	0	0.804617794	1.9478	4.439297794	3.1235
41	GL	0	1	1	1.970133284	0.40894	7.223733284	1.178
42	GL	0	1	1	2.077930748	0.4097	6.690630748	1.0124
43	GL	0	1	1	1.757843959	0.40054	8.366443959	1.5144
44	GL	0	1	1	1.826198325	0.39291	6.919598325	1.123
45	GL	0	1	1	1.586146486	0.39978	9.830146486	1.9264
51	GL	0	1	0	2.202985873	0.087738	4.819885873	0.1236
52	GL	0	1	0	1.321101477	0.069427	7.632101477	0.2533
53	GL	0	1	0	1.948846032	0.07019	4.991546032	0.16937
54	GL	0	1	0	2.807823534	0.17624	5.540623534	0.32349
61	PC	1	0	0	0.284235842	0.18311	1.181235842	0.24185
62	PC	1	0	0	0.922222222	1.0757	1.303222222	1.5747
63	PC	1	0	0	0.659016213	2.0676	0.857016213	2.2545
64	PC	1	0	0	0.637493045	2.137	0.831493045	2.4834
65	PC	1	0	0	0.769440675	1.812	0.878440675	2.0798
71	PC	1	1	1	0.624673374	1.2367	9.793673374	2.7458
72	PC	1	1	1	0.800206527	2.079	7.333206527	3.418
73	PC	1	1	1	0.757422363	1.9012	13.15342236	3.9963
74	PC	1	1	1	0.936433402	2.565	4.109433402	4.1252
75	PC	1	1	1	0.952506748	2.0248	4.698506748	3.6545
81	PC	1	1	0	0.825485636	2.4208	2.023485636	3.2433
82	PC	1	1	0	0.909353355	2.2758	3.970353355	3.125
83	PC	1	1	0	1.111201293	2.3369	2.166201293	2.9015
84	PC	1	1	0	0.344444444	0.60272	1.392444444	1.4458
85	PC	1	1	0	1.003665984	2.2247	3.762665984	3.2433
91	PC	0	1	1	0.857663302	0.25406	17.2456633	3.6919
92	PC	0	1	1	0.654478678	0.2327	18.81347868	3.6064
93	PC	0	1	1	0.490448382	0.1976	14.41844838	3.241
94	PC	0	1	1	0.619769205	0.2327	11.5007692	2.6627
95	PC	0	1	1	0.688800403	0.18768	7.852800403	1.4008
101	PC	0	1	0	1.861267134	0.080872	3.631267134	0.14114
102	PC	0	1	0	1.672033069	0.099182	4.551033069	0.2182
104	PC	0	1	0	1.097488599	0.052643	5.014488599	0.21896
105	PC	0	1	0	1.035315793	0.32501	15.20631579	3.6926

```
t = -3.519, df = 36.796, p-value = 0.001172
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval: -0.7643583 -0.2057004
sample estimates:
mean of x mean of y
0.8547944 1.3398237
```

Here, t is the t value of the difference. The t value of a statistic is its mean divided by its standard deviation, so in other words the t value measures how many standard deviation out from 0 the mean is. The probability of the mean being this many standard deviations from 0 by accident, is the p value, and is calculated by means of the t value and the *df* ("degrees of freedom") in the t distribution.

In table 1, R has designated "mean of x" to be μ_{PC}, the mean of y_1 for glass type PC, and "mean of y" to be μ_{GL}, the mean of y_1 for glass type GL.

The *size* of the effect for factor x_1, glass type, on y_1, displacement at float, is the difference between the two means, $\varDelta_{11} = \mu_{PC} - \mu_{GL} = 1.3398237 -$

0.8547944 = 0.4850293. The other important finding is the probability that this result "or worse" could have been achieved by random data. This probability is called the p-value, and is $p = 0.001172$. Its significance level is $**$.

Table 2 summarizes the test results by the sizes and significances for the effects of the four factors on the four values.

Table 2: The effects and significance levels of the effects in pairwise t tests.

	x_1=Glass		x_2=Edge		x_3=Fugue		x_4=FugueEdge	
y_1=floatDisp	+0.485	($**$)	−0.614	($**$)	+0.388	($**$)	+0.939	
y_2=floatLoad	+0.257		+1.768	($***$)	−0.601	($*$)	−0.129	
y_3=topDisp	−1.254		−4.910	($***$)	+4.528	($***$)	+4.656	($***$)
y_4=topLoad	+0.076		+1.686	($***$)	+0.063		+0.887	($*$)

This is a useful result, and *Edge* stands out as both significant and with a large effect on all values. However, this method has its limitations, and works best if the causal effects of the factors are independent. There is no reason to make that assumption here, so instead, it is necessary to turn to a more efficient tool which does not require that assumption.

4.3 Analysis of Key Points, Take 2: Linear Regression and ANOVA

Equation 1 shows the basic linear model for y_k:

$$y_k = \beta_{k0} + \beta_{k1}x_1 + \beta_{k2}x_2 + \beta_{k3}x_3 + \beta_{k4}x_4 \tag{1}$$

Glass (type), Edge, Fugue, and FugueEdge are coded as so called *dummy variables*, with the latter three explicitly set as 0 or 1 in the data frame, and the Glass type implicitly set by R itself, to GL=0 and PC=1. Equation 2 shows the results of calculating the coefficients for y_4, max load.

$$y_4 = 0.422 - 0.094x_1 + 2.088x_2 + 0.465x_3 + 1.138x_4 \tag{2}$$

R's built-in linear regression method **lm** handles these calculations by means of the command

```
mod41 = lm(y4 ~ x1 + x2 + x3 + x4, data=tD)
```

The command **summary(mod41)** summarizes the output from **lm** in Table 3. According to Table 3, *Edge* and *FugueEdge* are significant at any conventional level of significance.

The first column, *Coefficients*, lists the coefficients β_{4i} in the regression equation, and since these variables are dummies with values 0 and 1, the coefficients are equal to the mean difference that those particular factor make. The coefficients are therefore the equivalent to the Δ_{4i} calculated in the previous section.

Table 3: R summary table for displacement at Max Load.

Coefficients	Estimate	Std. Error	t value	p =Pr($>|t|$)	Sign. Lvl
(Intercept) β_{40}	0.42158	0.45265	0.931	0.356996	
Glass, β_{41}	-0.09397	0.27711	-0.339	0.736232	
Edge, β_{42}	2.08825	0.31238	6.685	4.11e-08	***
Fugue, β_{43}	0.46526	0.40594	1.146	0.258224	
FugueEdge, β_{44}	1.13802	0.31332	3.632	0.000759	***

So β_{42}, for instance, stands for the mean effect of having adhesive on the edge as opposed to not having done it *in the presence of the other factors*. The next column, the *Std. Error*, lists the standard errors in the estimates of the coefficients.

The third column is the t value, which is sometimes called the *variability*. The variability is how many standard errors (col 2) away from 0 the estimate (col 1) is. So it is simply the value of the first column divided by the value of the second. The fourth and last column ($Pr(>|t|)$ is a probability calculation, where R uses the t distribution to find the probability that the the estimate could be this many standard errors (or more) away from 0 by pure chance. $Pr(>|t|$ is also called the p-value. When the p value is small, it means that the probability of erroneously concluding the presence of an effect from that factor is correspondingly small.

So far, this sounds like means and standard deviations again, but there is a vital difference, which is that the regression takes into account *the presence of the other factors*. This is easy to see in the numbers as well, in that for instance $\Delta_{44} = 0.887$, whereas $\beta_{44} = 1.138$. The full table for the β coefficients and their significance levels, given simple linear regression, is in Table 4. Factors that were

Table 4: The effects and their significance levels in simple linear regression.

	x_0	x_1	x_2	x_3	x_4
y_1	+1.597 $(***)$	−0.482 $(***)$	−0.570 $(***)$	+0.224	−0.196
y_2	+0.046	−0.287 $(*)$	+1.888 $(***)$	+0.233	+0.164
y_3	+5.572 $(***)$	+1.379	−3.953 $(***)$	+0.615	+3.648 $(***)$
y_4	+0.422	−0.094	+2.088 $(***)$	+0.465	+1.138 $(***)$

significant in Table 2 are non-significant in Table 4, and some effect sizes have changed their sign in the presence of the other factors. Since this is the more advanced analysis, it takes precedence, so in conclusion the first model with t testing was a only good first approximation.

However, simple regression is also an approximation. One way further is to omit factors not proven to be significant. For y_4, this means a linear model omitting x_1=Glass and x_3=Fugue:

```
mod42 = lm(y4 ~ x2 + x4, data=tD)
summary(mod42)
```

The summary is in table 5. The coefficients are somewhat different, as should be expected since factors x_1=Glass and x_3=Fugue are no longer present.

Table 5: R summary table 2 for Max Load.

Coefficients	Estimate	Std. Error	t value	p =Pr(> $\|t\|$)	Sign. Lvl
(Intercept) β_0	0.7580	0.2726	2.781	0.00796	**
x2=Edge β_2	1.9573	0.2891	6.769	2.49e-08	***
x4=FugueEdge β_4	1.2854	0.2843	4.522	4.59e-05	***

A more thorough way further is to first complicate the model by looking at interactions between the factors, and only then removing the non-significant ones. To add a single interaction, like for instance between x_1=Glass and x_2=Edge, modify the R command with the interaction term x1:x2:

```
mod43 = lm(y4 ~ x1 + x2 + x3 + x4 + x1:x2, data=tD)
```

To add *all* k'th order interactions, write (replace k by its value)

```
mod44 = lm(y4 ~ (x1 + x2 + x3 + x4)^k, data=tD)
```

The result of the command **summary(mod45)** would be a table of 16 rows displaying the effects and significance levels of interactions on par with the factors on their own. The interesting result in that table is that the conventionally significant factors are x_2=Edge ($***$), x_4=FugueEdge ($*$) and $x_1 : x_2$ ($*$). Glass itself is highly non-significant with a p-value of 0.940.

Since the interaction terms soak up some of the variation, both the coefficients and the p-values change somewhat from those of the simple regression.

To proceed, note that the p-values are the likelihood that the coefficients in question actually differ from 0, *given the model*. The next logical step is to consider the model itself, more precisely the likelihood that the model captures as much variability as it does.

Data has variability, and the variability may be classed into two types: variability explained by the model, and variability unexplained by the model. Adding a new explanatory factor will explain more, and thus increase the part explained by the model. The tool ANOVA (Analysis Of Variance) analyses the contribution by the added factor (or interaction of factors).

ANOVA can compare just two models, or it can look at an entire hierarchy of models, built from the bottom and up. The simplest is Type I ANOVA (R command: **anova**), and is the easiest to understand. It is however, dependent on the order in which the factors are entered, so it is not the best. Type II ANOVA (R command: **Anova**, found in the R library *car*) does not have this problem.

The analysis of the models for y_4 uses Type II. Table 6 summarizes the results of the R command **Anova(mod45)**.

Table 6: R's ANOVA table for the factors explaining Max Load.

Coefficient	Sum Sq	Df	F value	Pr($> F$)	Sign. Lvl
Edge	40.065	1	68.1300	6.502e-10	***
Fugue	2.292	1	3.8980	0.0558445	.
FugueEdge	11.545	1	19.6320	8.055e-05	***
Glass	0.121	1	0.2051	0.6532458	
Edge:Fugue		0			
Edge:FugueEdge	1.222	1	2.0783	0.1578147	
Edge:Glass	8.346	1	14.1929	0.0005746	***
Fugue:FugueEdge		0			
Fugue:Glass	0.720	1	1.2248	0.2755654	
FugueEdge:Glass	0.321	1	0.5458	0.4647200	
Edge:Fugue:FugueEdge		0			
Edge:Fugue:Glass		0			
Edge:FugueEdge:Glass	0.257	1	0.4370	0.5126844	
Fugue:FugueEdge:Glass		0			
Edge:Fugue:FugueEdge:Glass		0			
Residuals	21.758	37			

In Table 6 the first column is Sum Sq, meaning *Sum of square deviations*. It sums the squares of the improvement in prediction for each coefficient added, as more coefficients are added through progressing down the list. The Df is *degrees of freedom*. The F value is calculated from the Sum Sq and Df, and Pr(¿F) is the probability of getting an F value that large, or larger.

Both the ANOVA table and the summary table display the curious effect that *glass type* seems to be non-significant when considered on its own, but not when interacting with the factor of edge adhesive! This is, however, not difficult to interpret, since this means that glass type does not matter *when averaged for the presence and non-presence of edge adhesive*, but that one type of glass boosts the effect of edge adhesive whereas the other glass type diminishes it. Table 7 shows the effect of Edge+Glass+Glass:Edge.

Table 7: Glass and Edge interaction term.

	No Edge adhesive	Edge adhesive
GL	0 + 0 + 0 = 0	3.0524 + 0 + 0 = 3.26389
PC	0 + 1.2500 + 0 = 1.2500	3.0524 + 1.2500 - 2.1649 = 2.1375

But first, which is the better choice? It is in general a bad idea to include an interaction of factors without including the factors, so if glass:edge is in, so is glass itself. For the other factors, choose generously at a significance level of 0.1 for a final model for the max load of

```
mod4Final = lm(y4 ~ x1 + x2 + x4 + x1:x2, data=tD)
```

The final linear formula for the factors is then in equation 3

$$y_4 = 0.141 + 1.250x_1 + 3.052x_2 + 1.271x_4 - 2.165x_1x_2 \tag{3}$$

4.4 The Other 3 Values and Summary

The other analyses proceed in the same way, by looking at interactions as well as the factors themselves, and then pruning down as far as possible. The resulting formulas for the sizes of the effects of the conventionally significant factors and interactions are then captured in these formulas. The significance levels (. $*$ $**$ and $***$) are written below their respective coefficients:

$$\begin{array}{lccccccc} y_1 = & 2.137 & -\,0.787x_1 & -\,1.284x_2 & -\,0.346x_4 & +\,0.707x_1x_2 & -\,0.288x_1x_4 & +\,0.622x_2x_4 \\ & *** & *** & *** & * & *** & . & *** \end{array}$$

$$\begin{array}{lcccc} y_2 = & 0.053 & -\,0.290x_1 & +\,1.883x_2 & +\,0.319x_3 \\ & & * & *** & . \end{array}$$

$$\begin{array}{lcccccc} y_3 = & 6.201 & +\,1.195x_1 & -\,2.476x_2 & +\,1.241x_4 & -\,3.201x_1x_2 & +\,5.093x_1x_4 \\ & *** & & * & & * & ** \end{array}$$

$$\begin{array}{lccccc} y_4 = & 0.141 & +\,1.250x_1 & +\,3.052x_2 & +\,1.271x_4 & -\,2.165x_1x_2 \\ & & ** & *** & *** & *** \end{array}$$

Two factors were present to explain all four values: x_1=Glass type, and x_2=Edge adhesive. Of these, x_2 was by far both the most signficant *and* the one with the greatest effect. Among the remaining two, x_3=Fugue, was the least significant, and x_4=FugueEdge (extended fugue adhesive) mattered only for the value of the max load, beyond the float point. However, in interaction with glass type, x_4 did have a strong effect on the displacements (y_1 and y_3).

5 Concluding Remarks

This paper investigated the effects of adhesion between aluminium profiles and glass from a static tensile standpoint, with view to applying these insights to calculations of structural strength. The key elements under study were the displacement and loads at two critical points to strength calculations. The key takeaway result is that the edge adhesive is the most important contributor to both points, and that the glass type makes an appreciable difference to the adhesion as well. Theoretically, this paper looked at two different forms of statistical analysis, pairwise *t*-tests, and regression analysis with ANOVA. The latter is by far the more robust and detailed tool, and reversed some conclusions from the simpler *t*-test, most notably when the *t*-test concluded that the presence of fugue adhesive was a key contributor to both points of structural strength. The regression analysis also showed that the effect of "fugue edge" depends on glass type and on edge adhesive. As future work, intelligent optimisation and machine learning (ML) techniques [3] may be applied to better understand the considered process.

6 Acknowledgements

The authors want to thank Geir Horst Søraker and Arne Skjølingstad at Ertec AS for producing the test samples and for valuable discussions.

References

1. Bedon, C., Louter, C.: Structural glass beams with embedded gfrp, cfrp or steel reinforcement rods: Comparative experimental, analytical and numerical investigations. Journal of Building Engineering **22**, 227–241 (2019)
2. Fiore, V., Calabrese, L., Proverbio, E., Galtieri, G., Scalici, T., Lo Presti, V., Valenza, A.: Pull-off adhesion of hybrid glass-steel adhesive joints in salt fog environment. Journal of adhesion science and Technology **30**(19), 2157–2174 (2016)
3. Hatledal, L.I., Sanfilippo, F., Zhang, H.: Jiop: A java intelligent optimisation and machine learning framework. In: Proc. of the 28th European Conference on Modelling and Simulation (ECMS), Brescia, Italy. pp. 101–107 (2014)
4. Kwon, D.J., Kim, J.H., Kim, Y.J., Kim, J.J., Park, S.M., Kwon, I.J., Shin, P.S., DeVries, L.K., Park, J.M.: Comparison of interfacial adhesion of hybrid materials of aluminum/carbon fiber reinforced epoxy composites with different surface roughness. Composites Part B: Engineering **170**, 11–18 (2019)
5. Louter, C., Belis, J., Bos, F., Veer, F.: Reinforced glass beams composed of annealed, heat-strengthened and fully tempered glass. In: Challenging Glass 3, pp. 691–702. IOS Press (2012)
6. Machado, J., Nunes, P., Marques, E., da Silva, L.F.: Adhesive joints using aluminium and cfrp substrates tested at low and high temperatures under quasi-static and impact conditions for the automotive industry. Composites Part B: Engineering **158**, 102–116 (2019)
7. Machalická, K., Eliášová, M.: Adhesive joints in glass structures: effects of various materials in the connection, thickness of the adhesive layer, and ageing. International Journal of Adhesion and Adhesives **72**, 10–22 (2017)
8. Marchione, F., Munafò, P.: Experimental strength evaluation of glass/aluminum double-lap adhesive joints. Journal of Building Engineering **30**, 101284 (2020)
9. Martens, K., Caspeele, R., Belis, J.: Load-carrying behaviour of interrupted statically indeterminate reinforced laminated glass beams. Glass Structures & Engineering **1**(1), 81–94 (2016)

10. Overend, M., Jin, Q., Watson, J.: The selection and performance of adhesives for a steel–glass connection. International Journal of Adhesion and Adhesives **31**(7), 587–597 (2011)
11. Trzepiecinski, T., Kubit, A., Kudelski, R., Kwolek, P., Obłój, A.: Strength properties of aluminium/glass-fiber-reinforced laminate with additional epoxy adhesive film interlayer. International Journal of Adhesion and Adhesives **85**, 29–36 (2018)