



February 24-27, 2019

Developing Structure-Process-Property Relationships using Multivariate Analysis

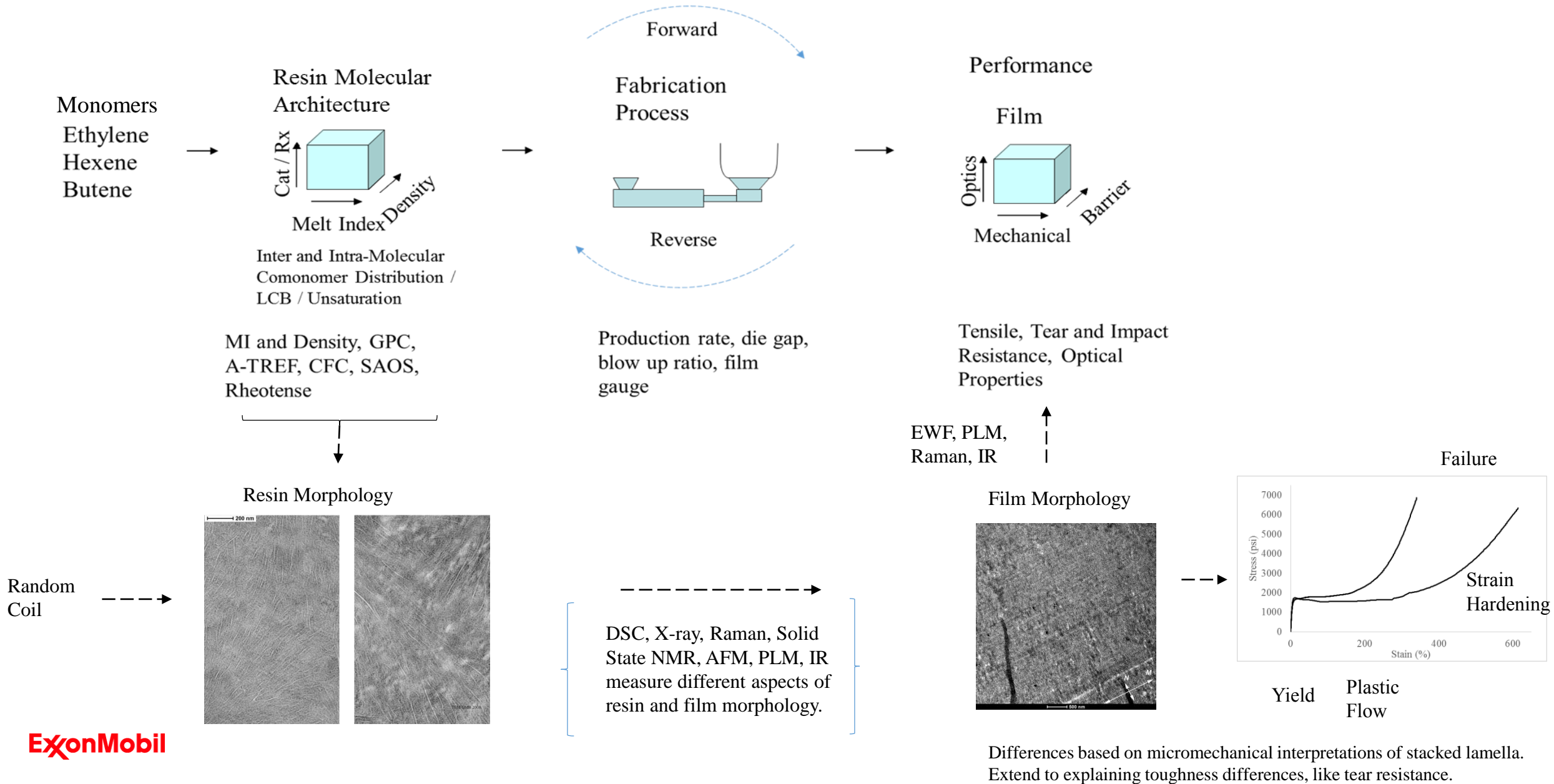
Energy lives here™

D. M. Fiscus

(David.M.Fiscus@ExxonMobil.com)

This presentation includes forward-looking statements. Actual future conditions (including economic conditions, energy demand, and energy supply) could differ materially due to changes in technology, the development of new supply sources, political events, demographic changes, and other factors discussed herein (and in Item 1A of ExxonMobil's latest report on Form 10-K or information set forth under "factors affecting future results" on the "investors" page of our website at www.exxonmobil.com). This material is not to be reproduced without the permission of Exxon Mobil Corporation.

Overview



Structure-Process-Property Analysis

Molecular Architecture and Morphology

Part Performance

Molecular Architecture / Morphology

Spectroscopic

Solution

Melt

Spectroscopic

Fabrication Control Variables

Fabrication Quality Variables

Engineering: Tensile, Tear, Impact, Optics, Barrier

Mechanics (EWF) Micromech

IR
NMR (^1H , ^{13}C , SS)
Raman
X-Ray
PLM

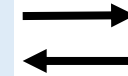
Melt Index
Density
Additives

GPC
TREF
CFC

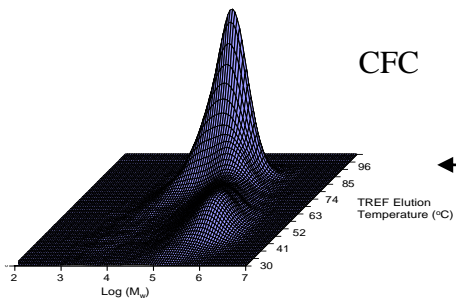
ODR
Rheotense
DSC

IR
NMR (^1H , ^{13}C , SS)
Raman
X-Ray
PLM

Production Rate,
Temp,
Die Gap
Blow-up Ratio
Gauge

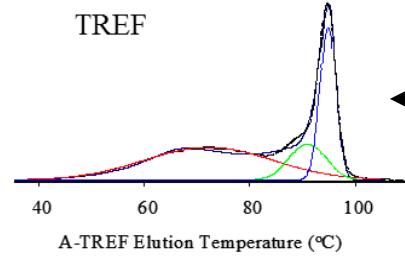


Temp,
Pressures
Torque



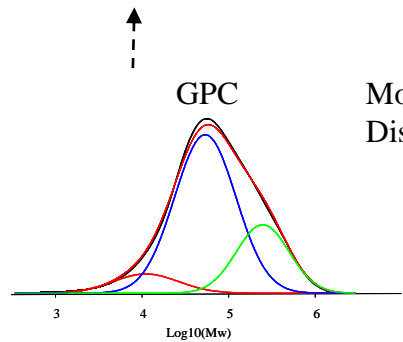
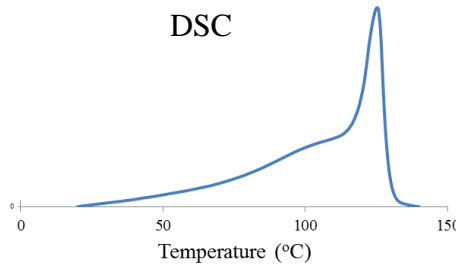
Comonomer Distribution

TREF

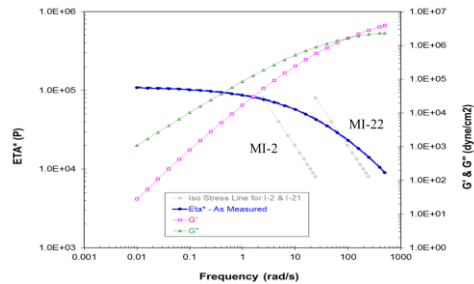


Heat Flow (mW/mg)

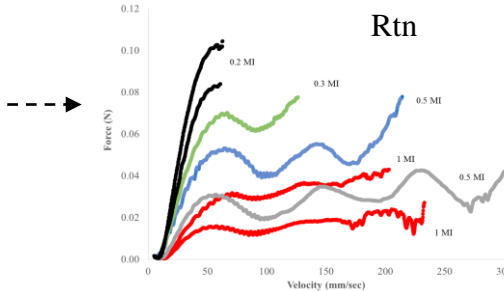
DSC



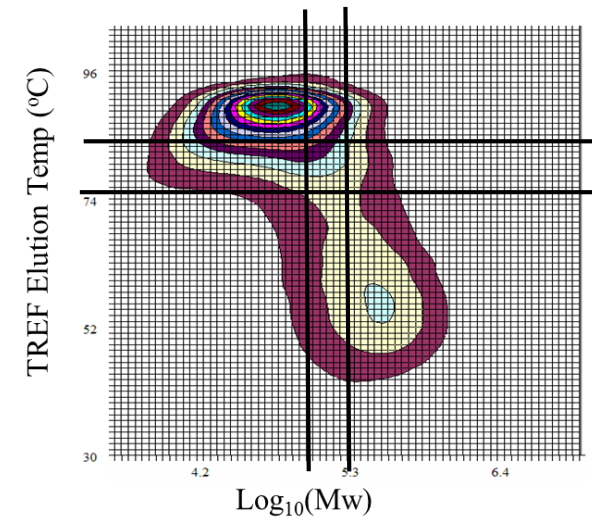
Molar Mass Distribution



G' & G'' (dynes/cm²)



Contour Plot of Molar Mass / Chemical Composition



Bin Results

CFC Plot

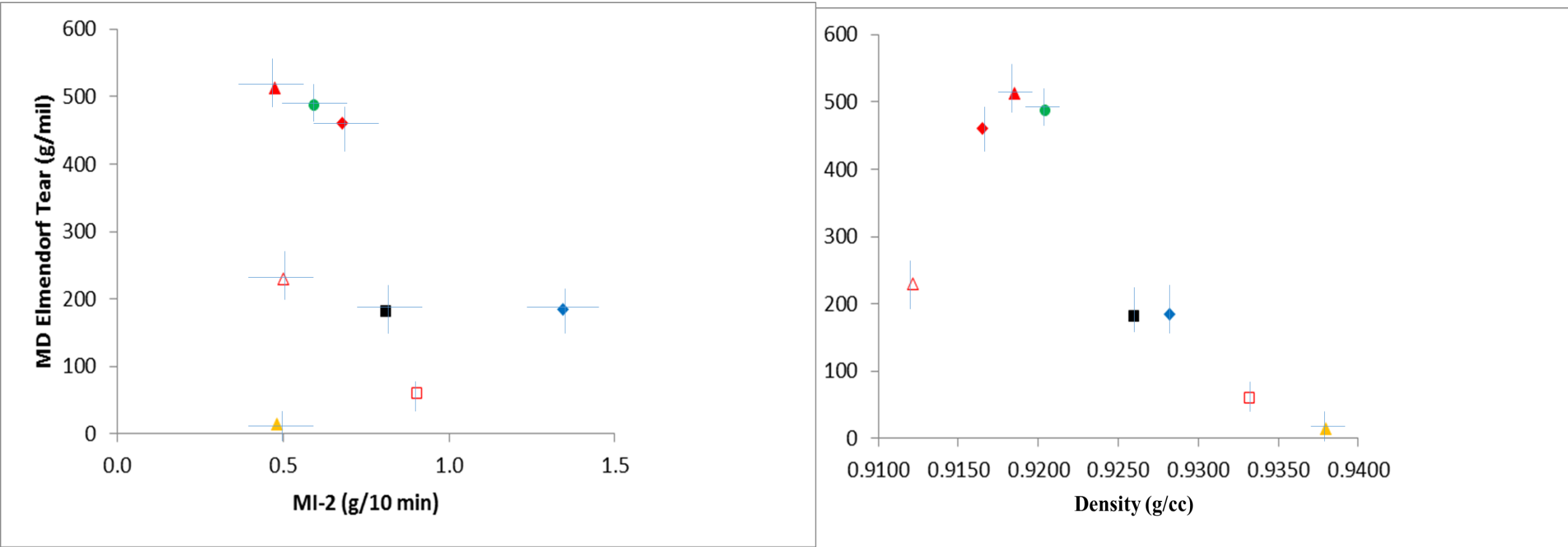
ExxonMobil

Cross Model

Double Reptation Theory

Univariate Analysis

Relationships use different measurement scales.
Relationships are general and not always monotonic.

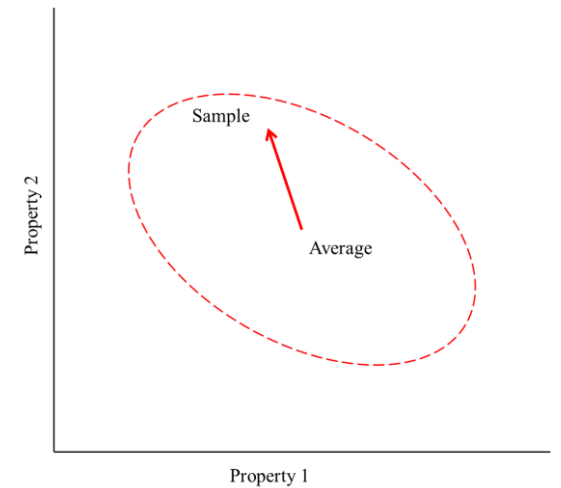
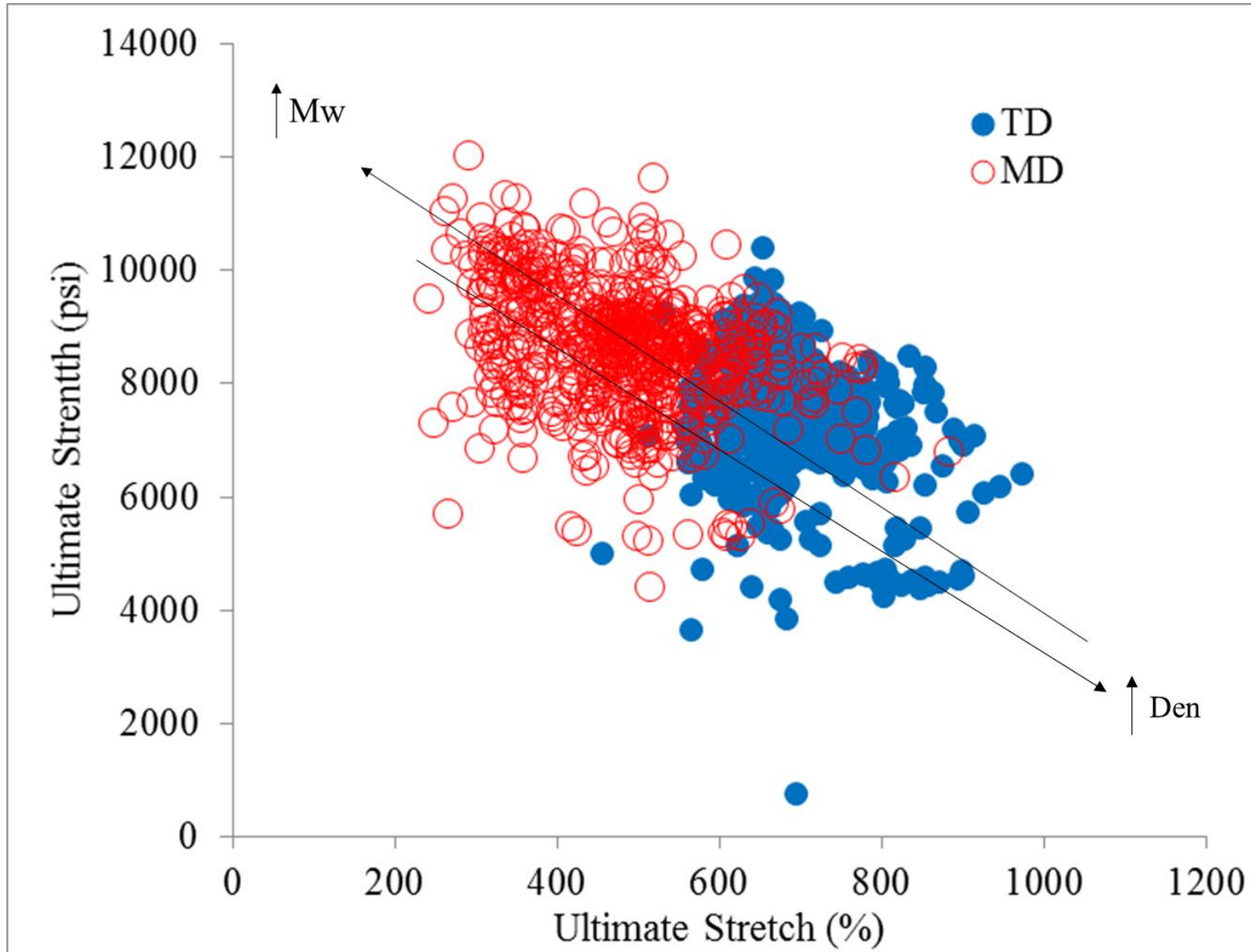


Average of selected samples.

ExxonMobil

Overlay Plot of Univariate Results

Liner PE Films ; > 0.89 Den, 90-400 K Mw, Pd < 11

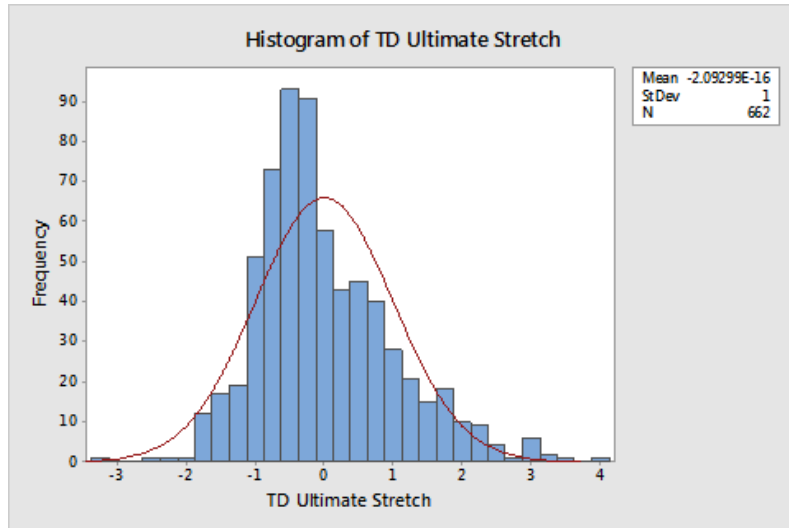


Statistical Analysis

Statistics removes differences due to measurement scales: variable effects are on equal footing.

Statistics describe populations

Performance increases with normalized values:
Distance and direction depict performance



Mean \approx most frequent value

Spread \approx four standard units of deviation

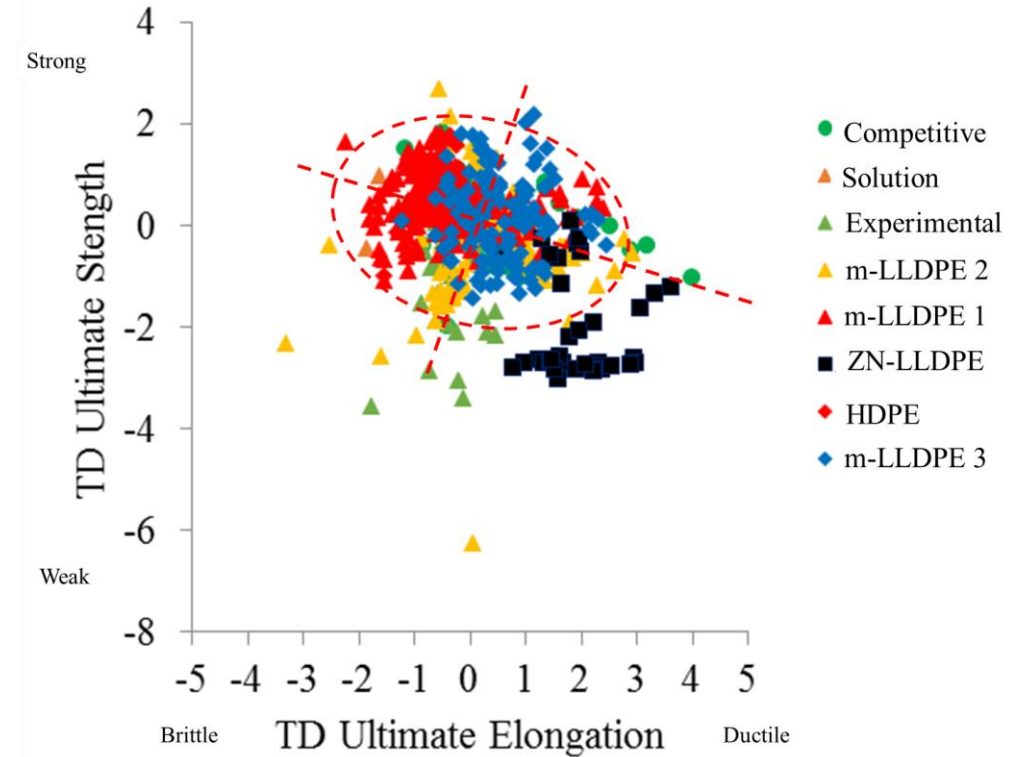
Values are mean centered and scaled to unit variation.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

x is the individual data value

μ is the data's average value

σ is the standard deviation



$$f(x) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho_{12}^2}} e^{-\frac{1}{2(1-\rho_{12}^2)}\left[\left(\frac{x_1-\mu_1}{\sigma_1}\right)^2 + \left(\frac{x_2-\mu_2}{\sigma_2}\right)^2 - 2\rho_{12}\left(\frac{x_1-\mu_1}{\sigma_1}\right)\left(\frac{x_2-\mu_2}{\sigma_2}\right)\right]}$$

x_i is the data's individual values

μ_i is their average values

σ_i is the standard deviation for their average values

ρ_{12} is their coefficient of correlation

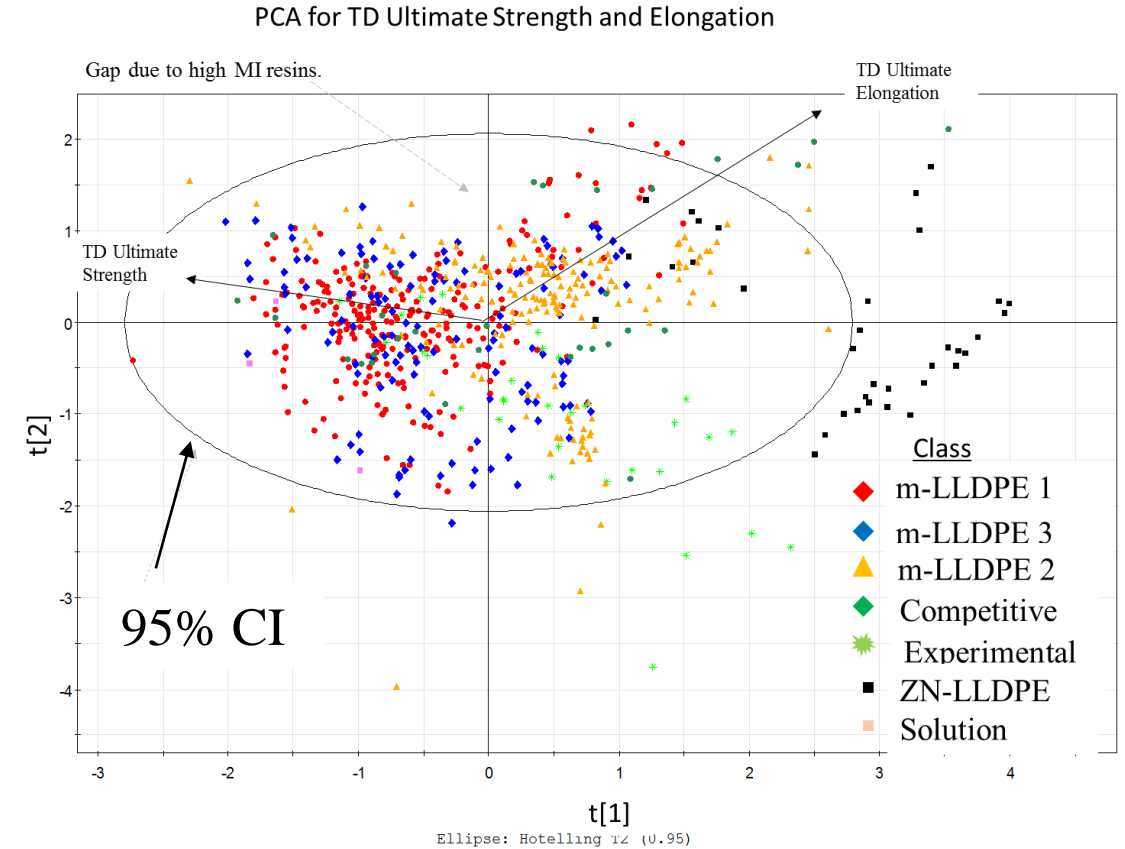
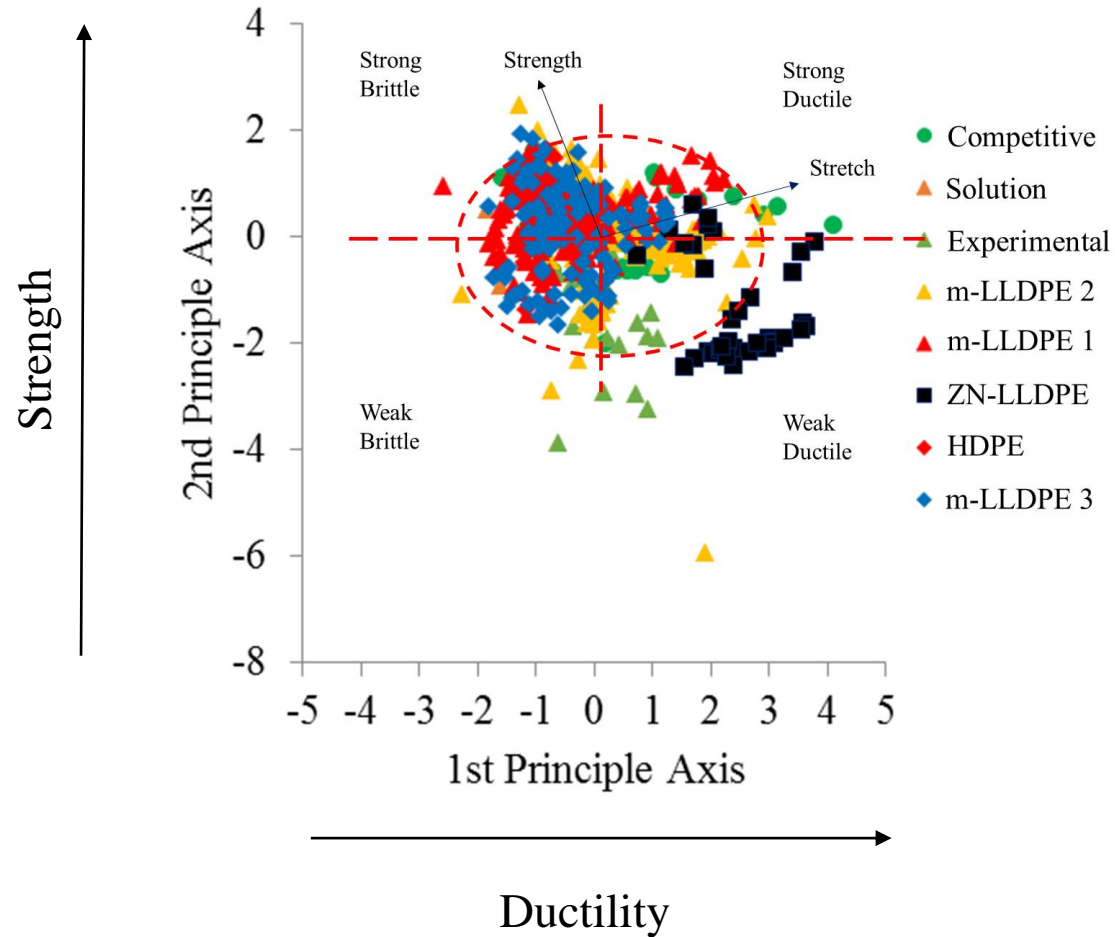
$$\rho_{12} = \frac{\text{cov}(x_1, x_2)}{\sigma_1\sigma_2} \text{ where } \text{cov}(x_1, x_2) = \sum (x_1 - \mu_1)(x_2 - \mu_2) / (n - 1)$$

n is the number of paired data points.

Dealing with Covariance

Principle axes reduces covariance.

Orthogonal axes eliminates covariance.



$$f(x) = \frac{1}{2\pi\sigma_1\sigma_2} e^{-\frac{1}{2}\left[\left(\frac{x_1-\mu_1}{\sigma_1}\right)^2 + \left(\frac{x_2-\mu_2}{\sigma_2}\right)^2\right]}$$

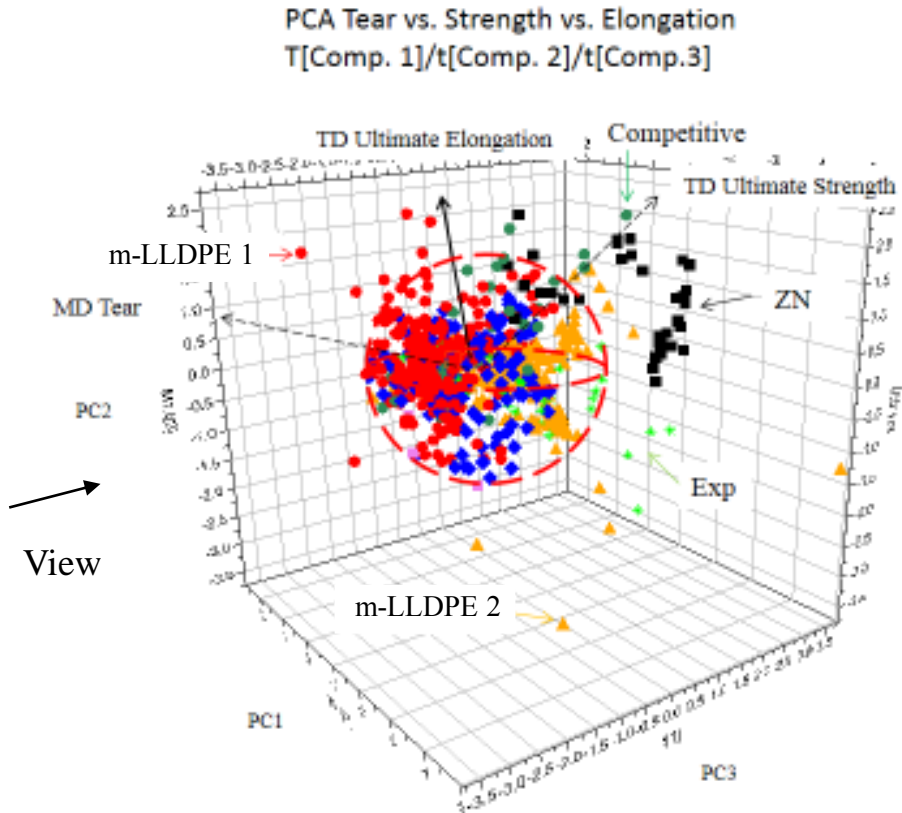
x_i is the individual data values

μ_i is their average value

σ_i is the standard deviation for those average values

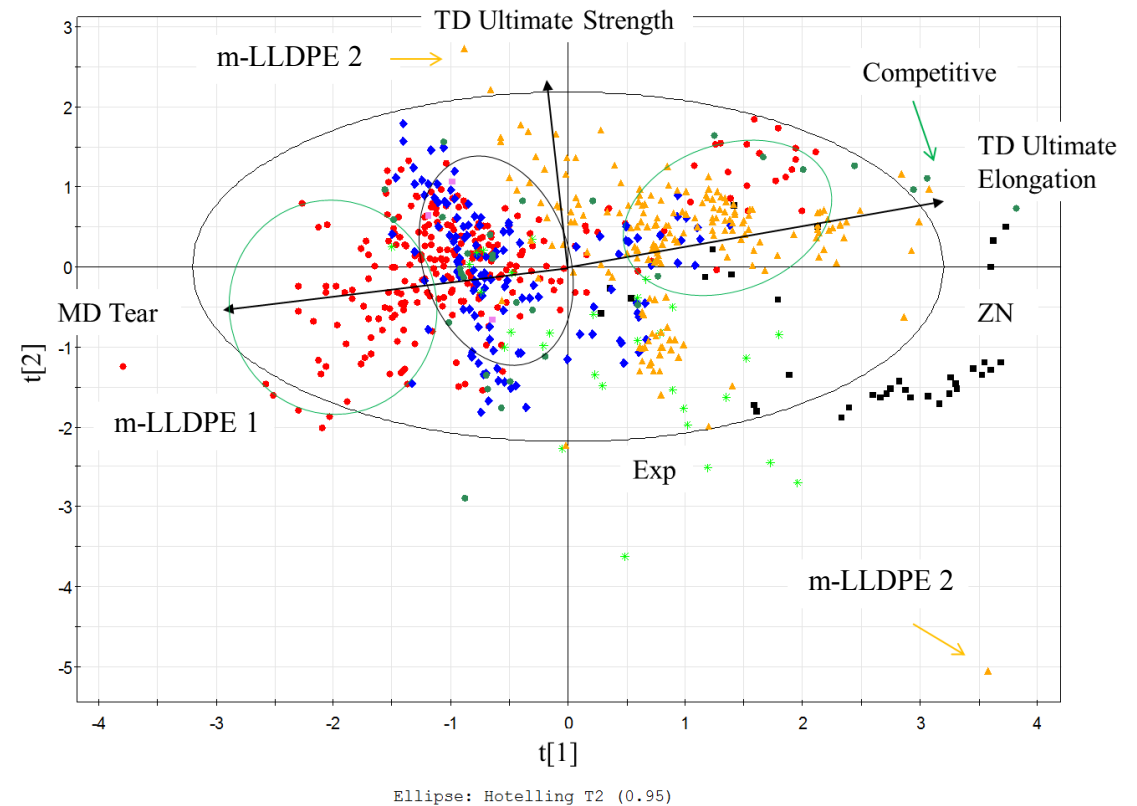
PCA of MD Tear Resistance and TD Ultimate Properties

3D PCA plot

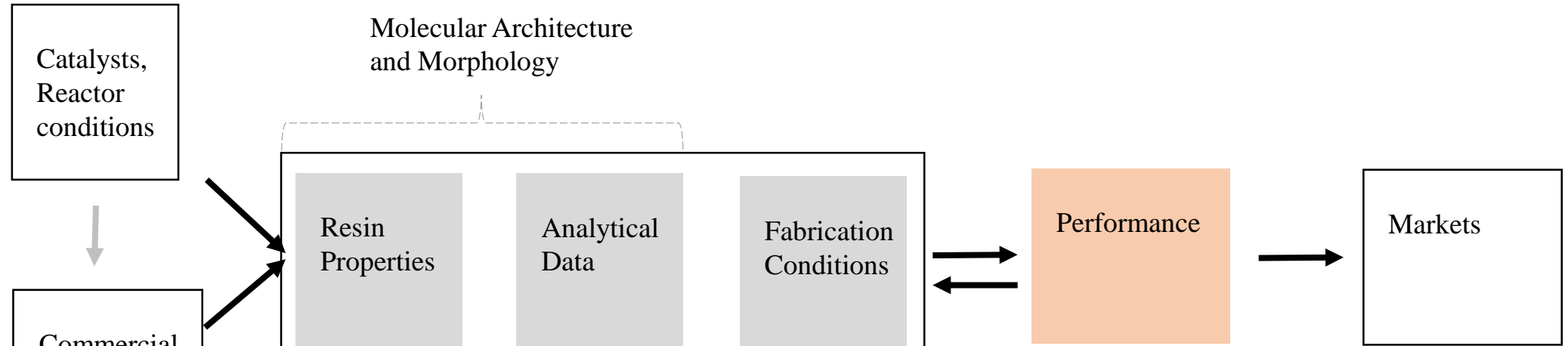


Projection onto coordinate planes gives bi-plots, like above.

PCA of MD Tear Resistance and Ultimate TD Performance

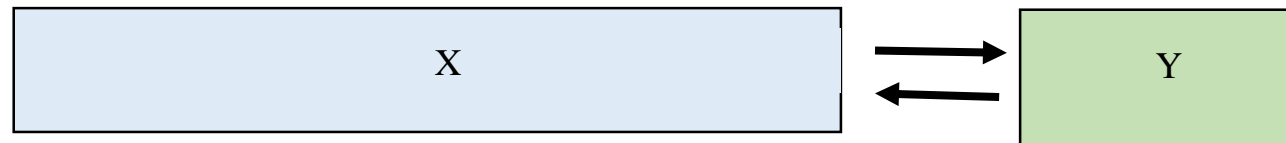


Process Map

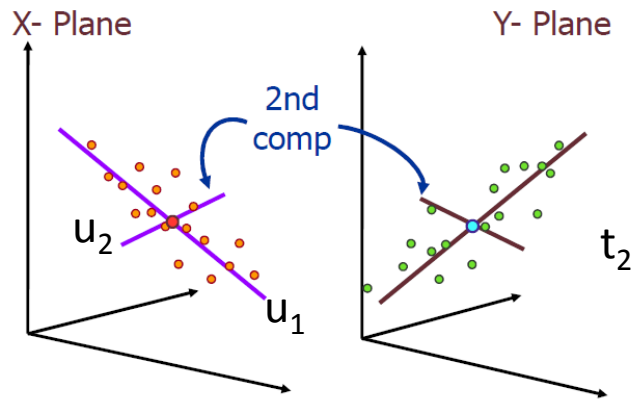
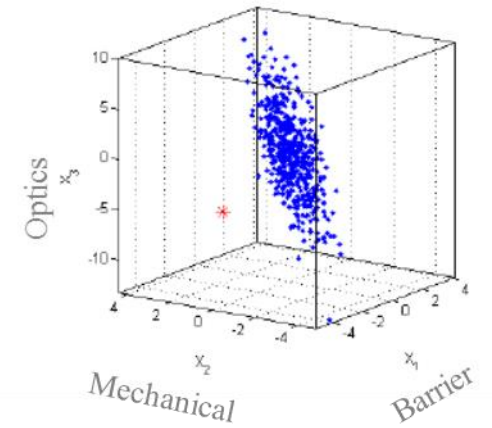
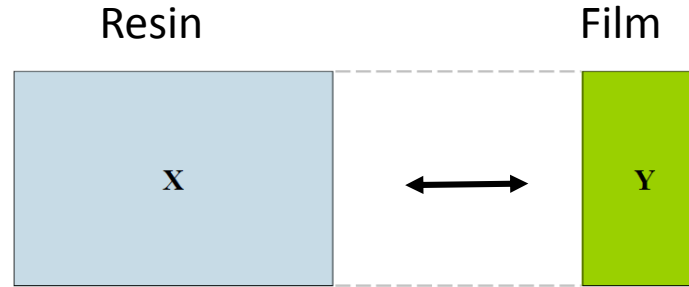
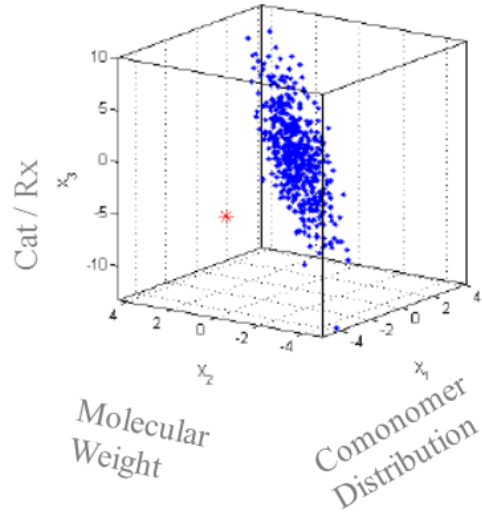


$$\begin{array}{c}
 \text{Resin 1} \\
 \text{Resin 2} \\
 \text{Resin 3} \\
 \vdots \\
 \text{Resin n}
 \end{array}
 \begin{bmatrix}
 \text{MI} & \text{Den} & \text{CFC} & \text{GPC} & \text{TREF} & \text{Draw} \\
 x_{11} & x_{12} & x_{13} & & \dots & x_{1q} \\
 x_{21} & x_{22} & x_{23} & & \dots & x_{2q} \\
 x_{31} & x_{32} & x_{33} & & \dots & x_{3q} \\
 \vdots & \vdots & \vdots & & \vdots & \vdots \\
 x_{n1} & x_{n2} & x_{n3} & & \dots & x_{nq}
 \end{bmatrix}
 \begin{bmatrix}
 \beta_{1q} \\
 \beta_{2q} \\
 \beta_{3q} \\
 \vdots \\
 \beta_{nq}
 \end{bmatrix}
 =
 \begin{bmatrix}
 \text{Stiff} & \text{Tear} & \text{Dart} & \text{Strength} & \text{Optics} \\
 p_{11} & p_{12} & p_{13} & \dots & p_{1m} \\
 p_{21} & p_{22} & p_{23} & \dots & p_{2m} \\
 p_{31} & p_{32} & p_{33} & \dots & p_{3m} \\
 \vdots & \vdots & \vdots & \vdots & \vdots \\
 p_{n1} & p_{n2} & p_{n3} & \dots & p_{nm}
 \end{bmatrix}$$

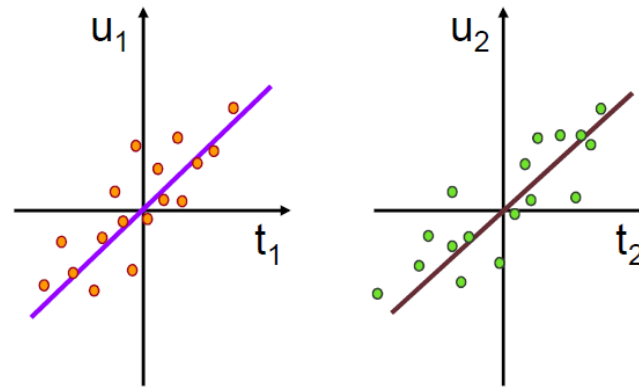
Focus



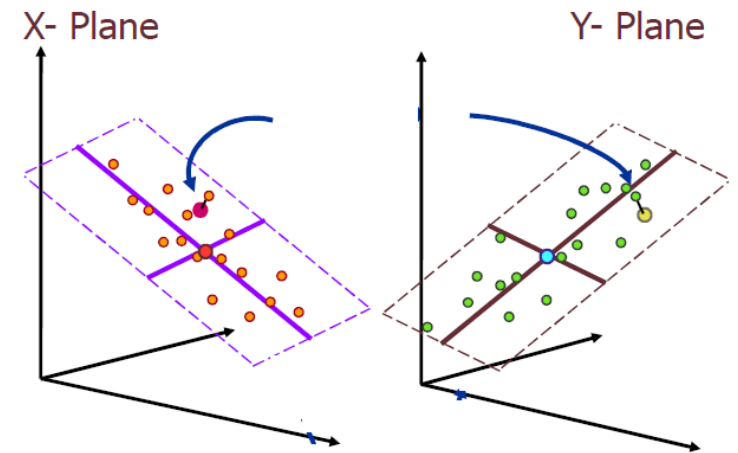
PLS Background



Principal Component Analysis

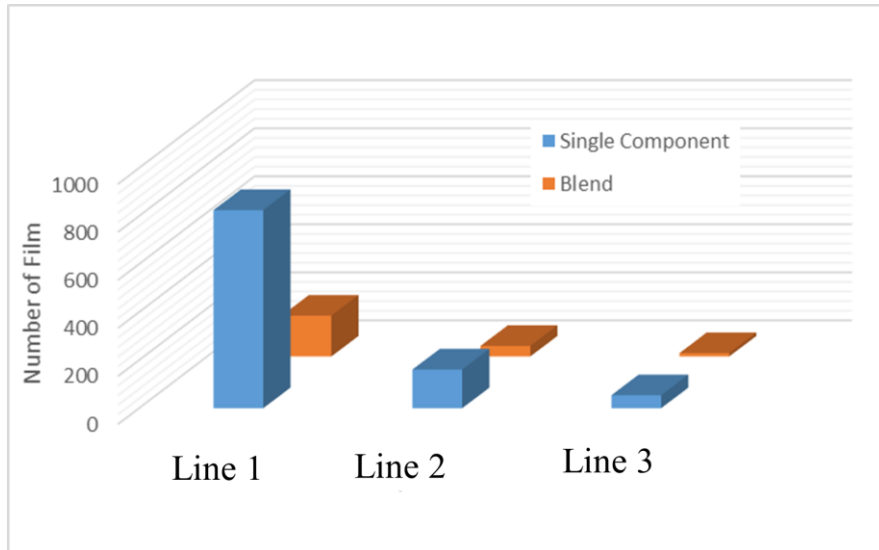
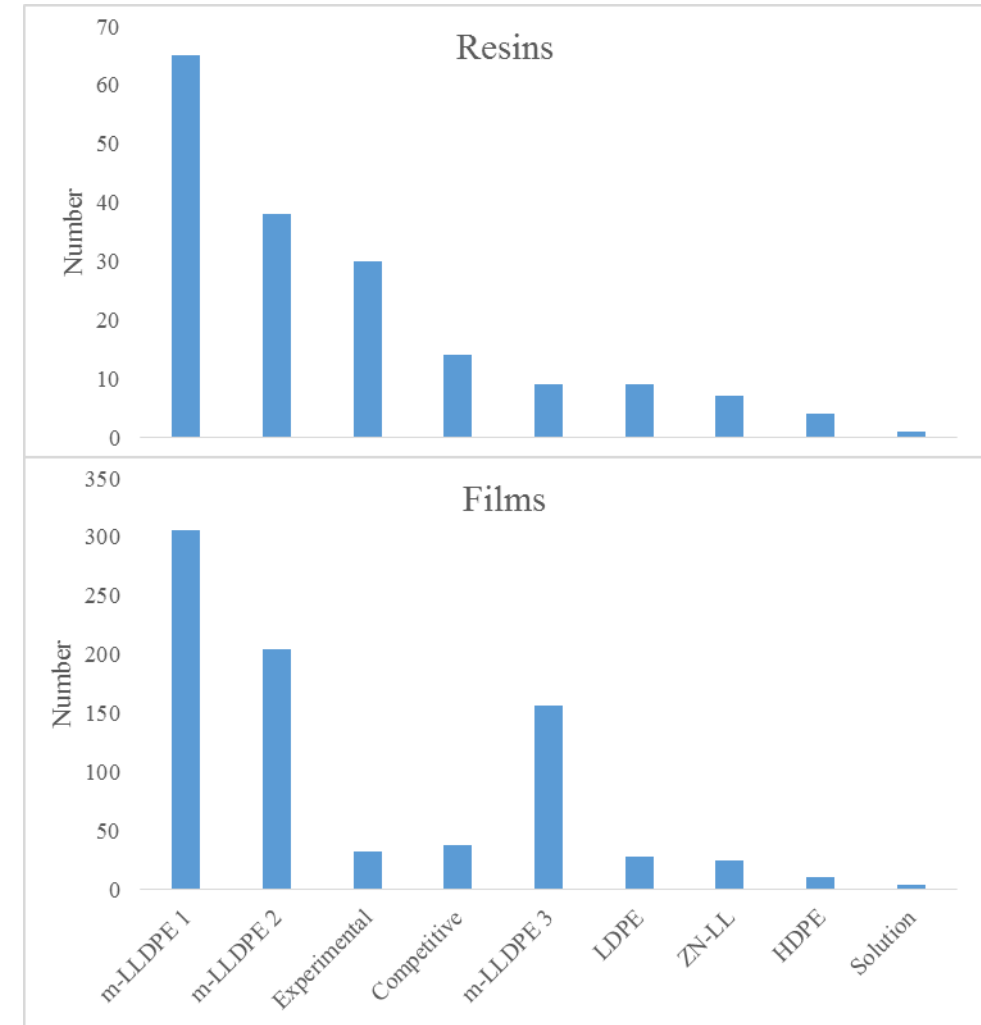


Principal Component Regression



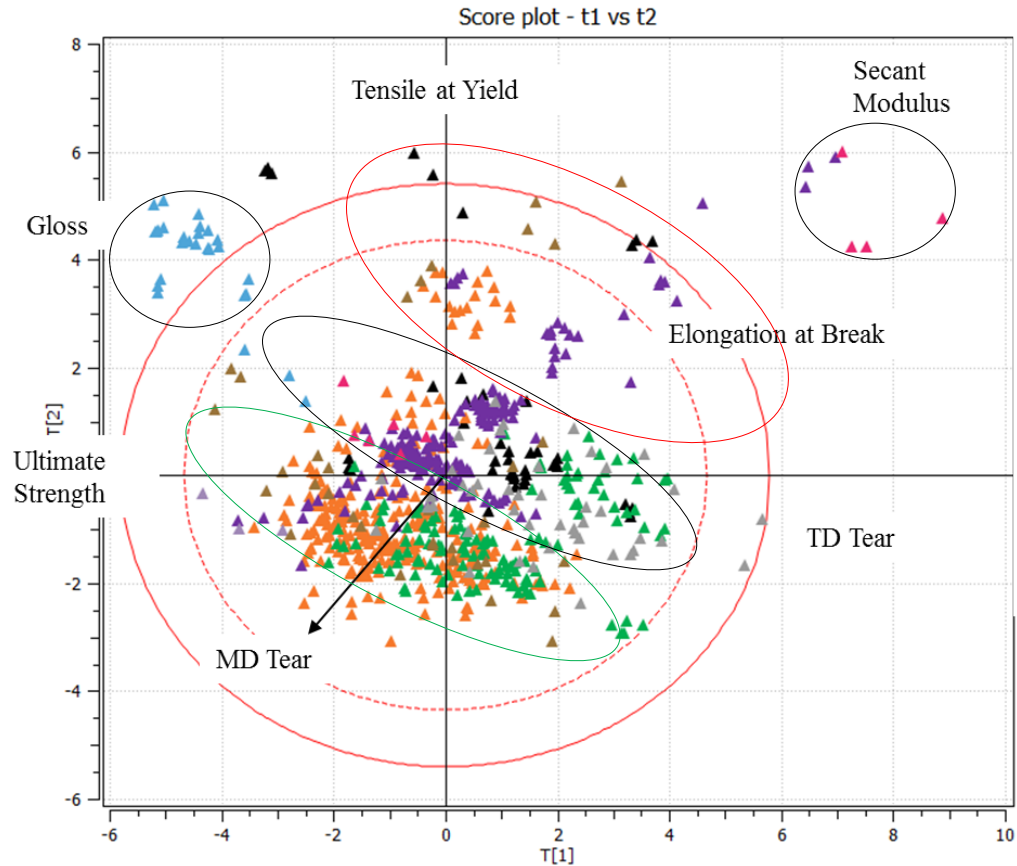
+ 1 K Films by Resins and Line

Resin Family	Density (g/cc)	I2 (g/10 min)	I21 (g/10 min)
Competitive	0.906 - 0.941	0.56 - 1.8	14 - 32
m-LLDPE 1	0.904 - 0.933	0.35 - 1.3	8 - 34
m-LLDPE 2	0.894 - 0.957	0.16 - 1.7	9 - 50
m-LLDPE 3	0.903 - 0.928	0.98 - 1.9	15 - 32
Experimental	0.917 - 0.932	0.46 - 1.2	18 - 65
ZN-LL	0.918 - 0.944	0.81 - 3.1	20 - 88
HDPE	0.958 - 0.961	0.45 - 0.7	28 - 32
Solution	0.900	1.2	
HP-LDPE	0.926 - 0.951	0.35 - 2.5	



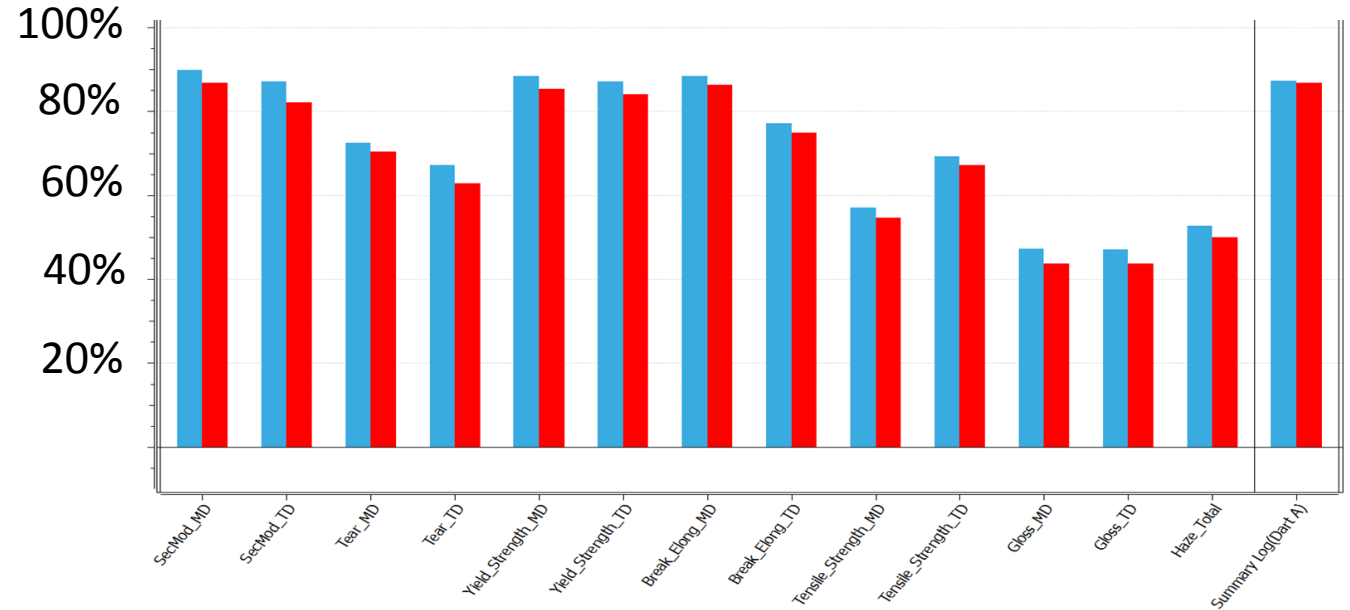
PCA for + 1 K Films

PCA Overlay Plot



Explains ($R^2(\text{cum})$) and predicts ($Q^2(\text{cum})$) > 70% of the variation in the film's balance of properties.

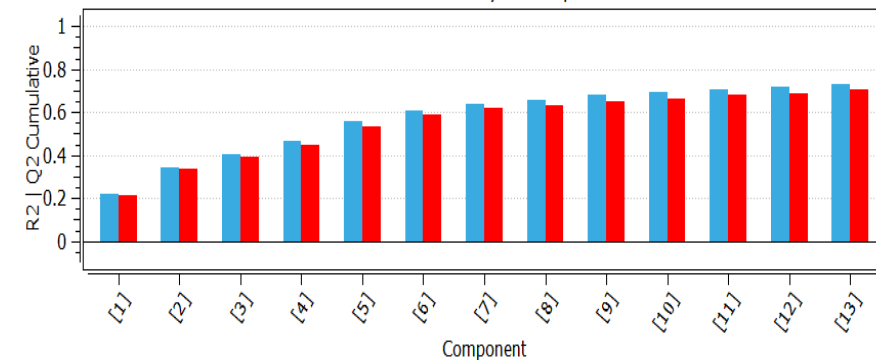
($R^2(\text{cum})$ and $Q^2(\text{cum})$) by performance variable.



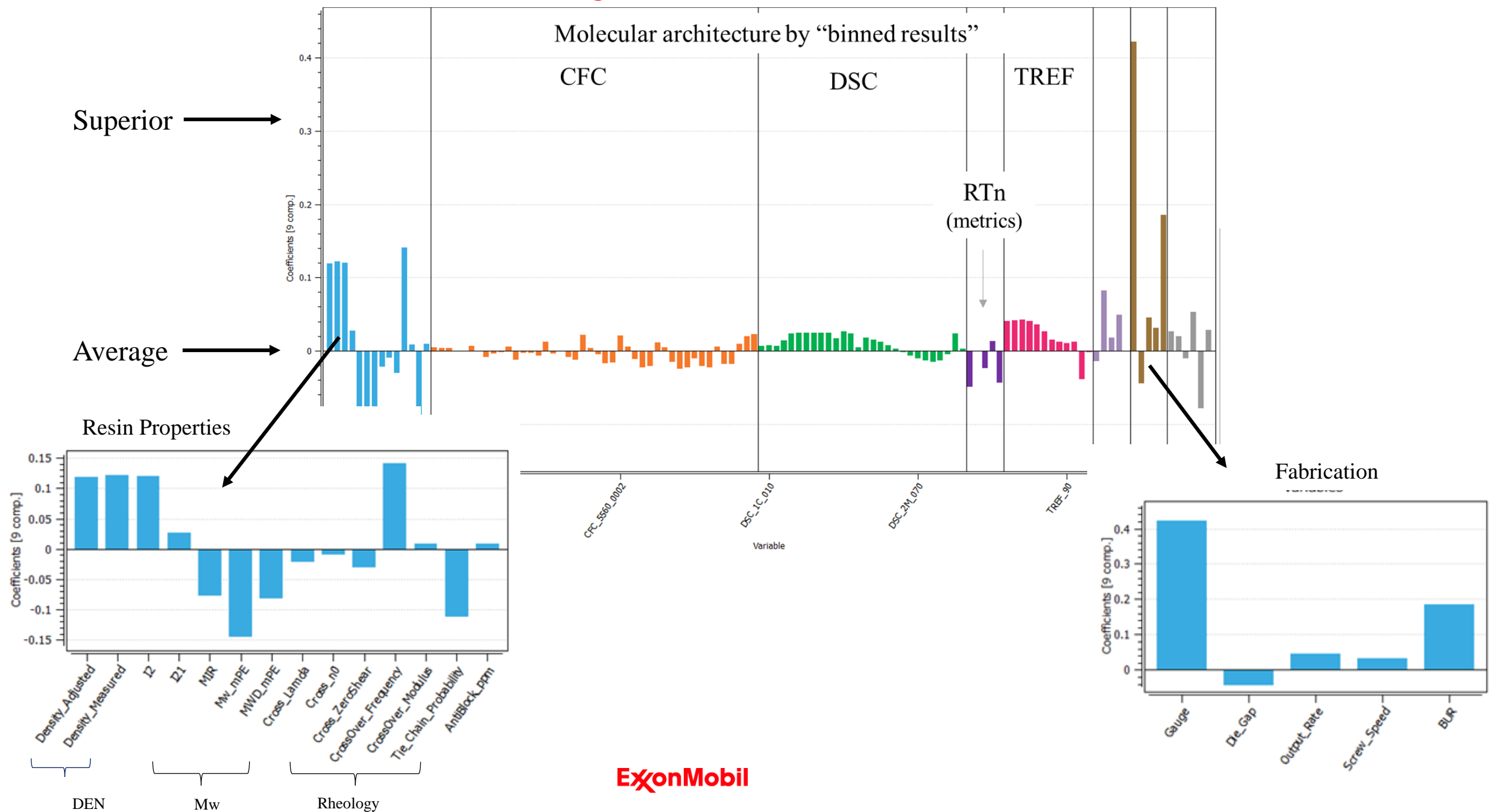
$R^2(\text{cum})$ are shown by blue bars.

$Q^2(\text{cum})$ are shown by red bars, calculated through cross validation

Model Summary for Y-Space

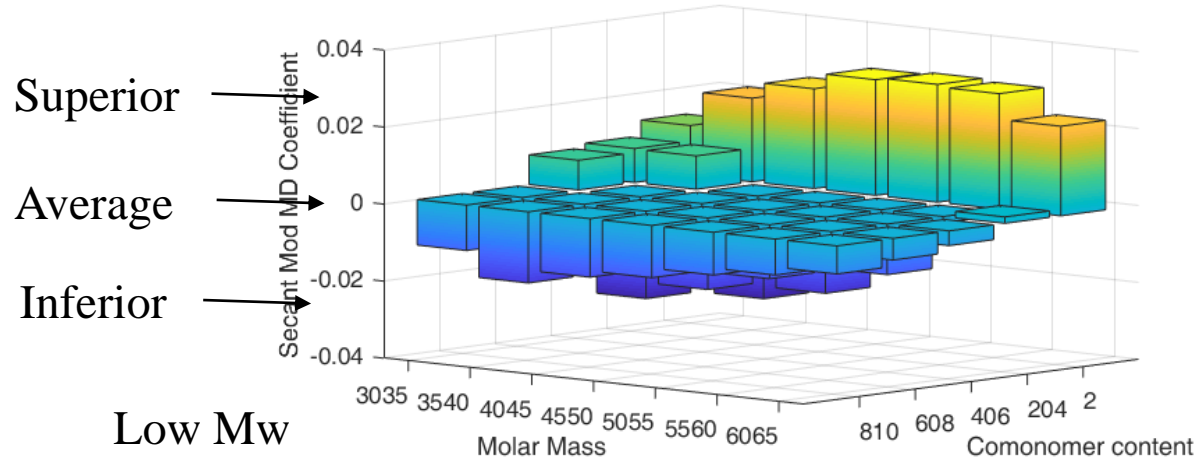


MD Elongation at Break Coefficient Plot

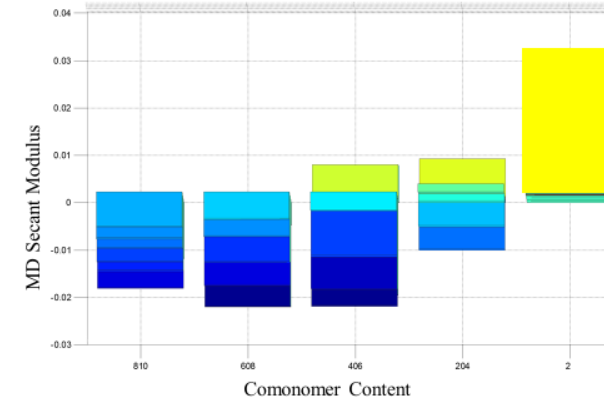


2D Coefficient Plots

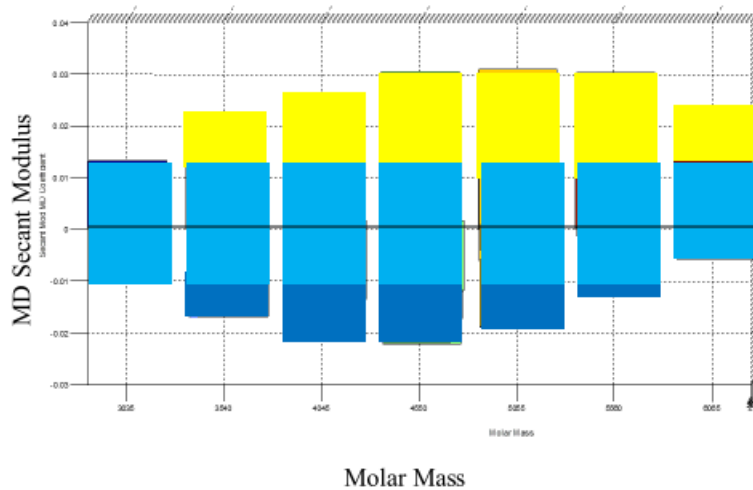
2D Coefficient Bar Graph
MD Secant Modulus vs. Molar Mass and Comonomer Content



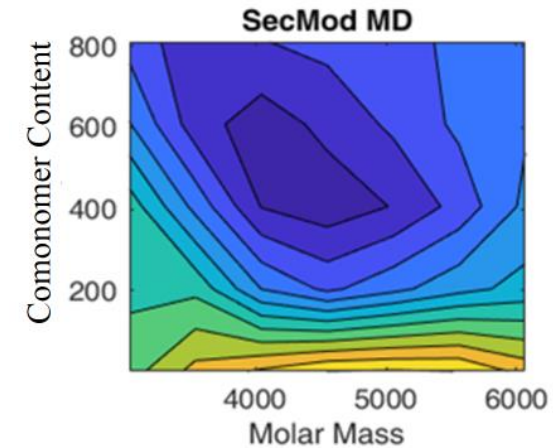
Coefficient Bar Graph
MD Secant Modulus vs. Comonomer Content



Coefficient Bar Graph
MD Secant Modulus vs. Molar Mass



Contour Plot
MD Secant Modulus vs. Molar Mass and Comonomer Content



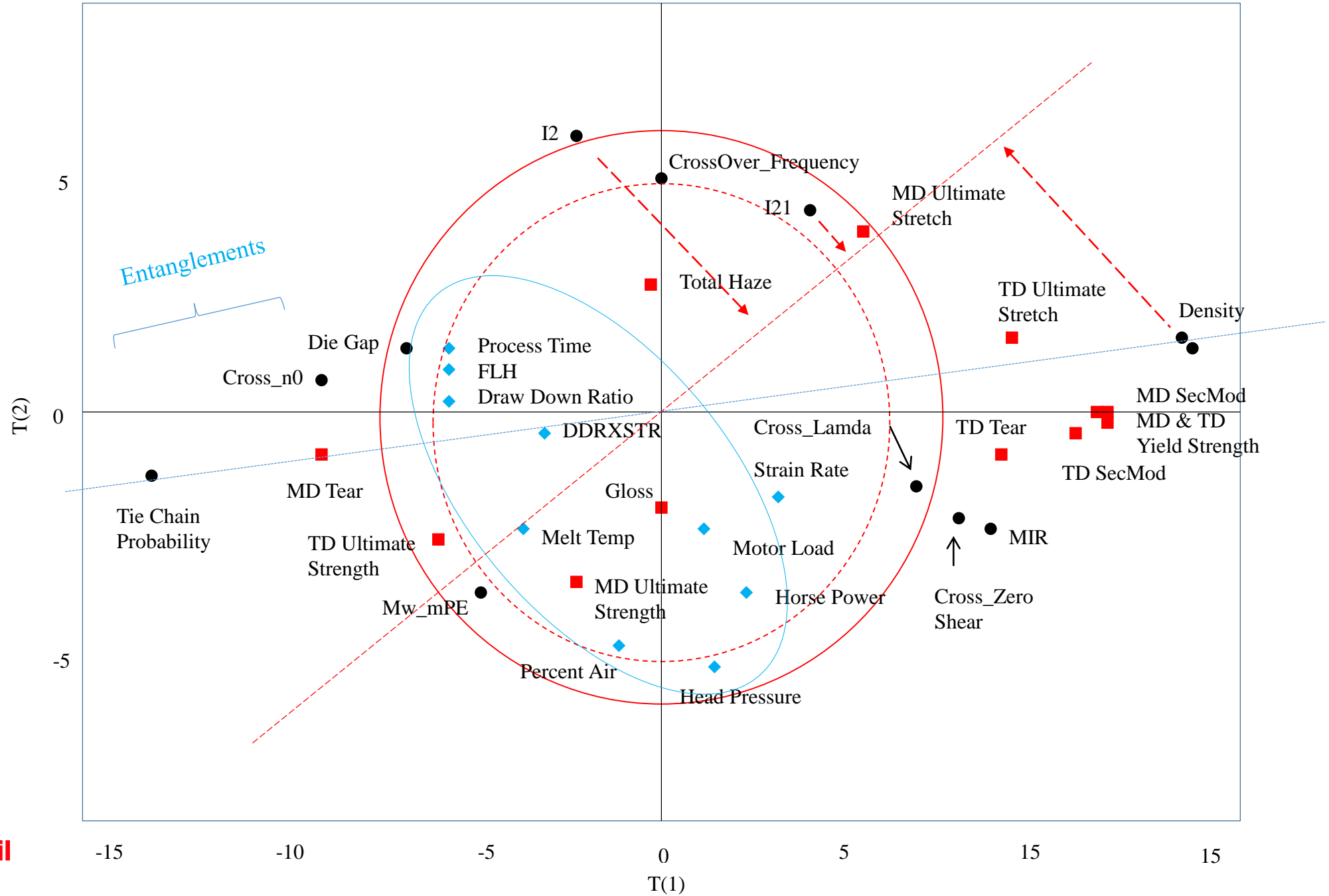
Comonomer Content



Comonomer Content

Comonomer Content

PLS Bi-plot (T[1]-T[2])



Summary

Film performance depends on resin molecular architecture and film fabrication conditions.

Information on a wide variety of films using a broad spectrum of commercial resins was presented.

Structure-process-property relationships for blown film resins were established using multivariate statistical methods of analysis.

Optimum balance of film properties is obtained for molecular architecture.

Fabrication dependent and independent models show resin molecular architecture affects film performance more than film fabrication conditions.

- Fabrication independent models explain about 50% of the total variation in film performance.
- Fabrication dependent models explain about 70% of the total variation in film performance.
- 20% to 30% of film performance is unexplained by the fabrication dependent model.
- Application to resin blends was shown.

ExxonMobil is using this technology in developing new blown film resins with superior balances of performance.

Data generated by or on behalf of ExxonMobil

Disclaimer

©2018 Exxon Mobil Corporation. To the extent the user is entitled to disclose and distribute this document, the user may forward, distribute, and/or photocopy this copyrighted document only if unaltered and complete, including all of its headers, footers, disclaimers, and other information. You may not copy this document to a Web site. ExxonMobil does not guarantee the typical (or other) values. Analysis may be performed on representative samples and not the actual product shipped. The information in this document relates only to the named product or materials when not in combination with any other product or materials. We based the information on data believed to be reliable on the date compiled, but we do not represent, warrant, or otherwise guarantee, expressly or impliedly, the merchantability, fitness for a particular purpose, suitability, accuracy, reliability, or completeness of this information or the products, materials, or processes described. The user is solely responsible for all determinations regarding any use of material or product and any process in its territories of interest. We expressly disclaim liability for any loss, damage, or injury directly or indirectly suffered or incurred as a result of or related to anyone using or relying on any of the information in this document. There is no endorsement of any product or process, and we expressly disclaim any contrary implication. The terms, “we”, “our”, "ExxonMobil Chemical", or "ExxonMobil" are used for convenience, and may include any one or more of ExxonMobil Chemical Company, Exxon Mobil Corporation, or any affiliates they directly or indirectly steward. ExxonMobil, the ExxonMobil Logo, the Interlocking “X” Device, and all other product names used herein are trademarks of ExxonMobil unless indicated otherwise.

Reduce Covariance Matrix into a Diagonal Matrix.

Linear Regression $y = a x + b$

Mean Centered $(y - \bar{Y}) = a (x - \bar{X})$

$$a = \frac{\text{Cov}(x, y)}{\text{Var}(x)}$$

Extends to multivariate analysis

$$\begin{bmatrix} s_{11}^2 & s_{12} & s_{13} & \cdots & s_{1m} \\ s_{21} & s_{22}^2 & s_{23} & \cdots & s_{2m} \\ s_{31} & s_{32} & s_{33}^2 & \cdots & s_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & s_{n3} & \cdots & s_{nm}^2 \end{bmatrix} \longrightarrow \begin{bmatrix} s_{11}^2 & & & & \\ & s_{22}^2 & & & \\ & & s_{33}^2 & & \\ & & & \ddots & \\ 0 & & & & s_m^2 \end{bmatrix}$$

$S \qquad \qquad \qquad L$

$$s(x_1, x_2) = \sum (x_1 - \mu_1)(x_2 - \mu_2)/(n - 1)$$

The covariance matrix is symmetric and non-singular. It is reduced using an orthonormal matrix U.

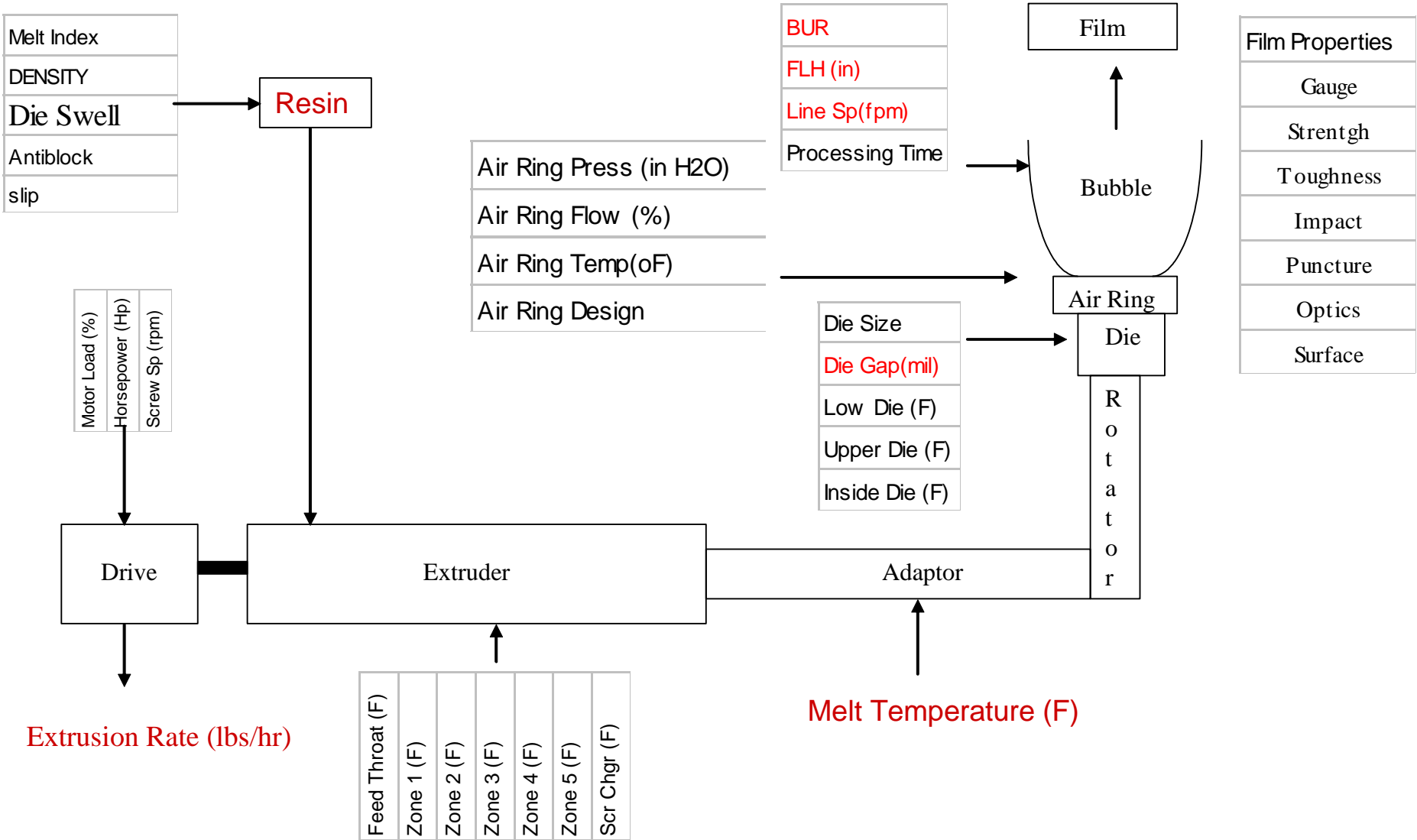
$U'SU = L$ Where the components of U are the Eigen vectors of S, and those of L are the Eigen values of S.

Solve $U'SU$ for the Eigen values of S using the characteristic equation: $|S - \lambda I| = 0$

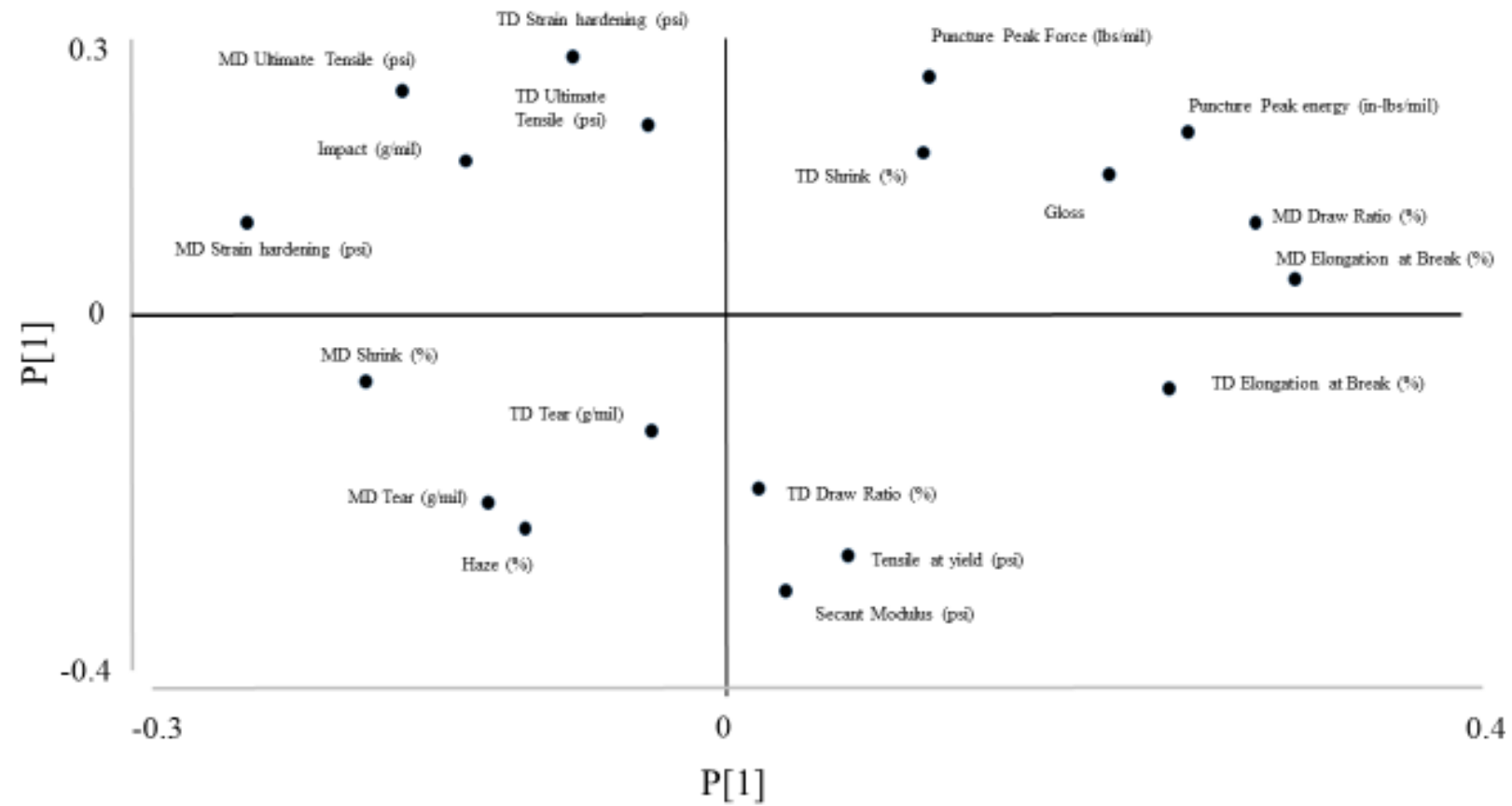
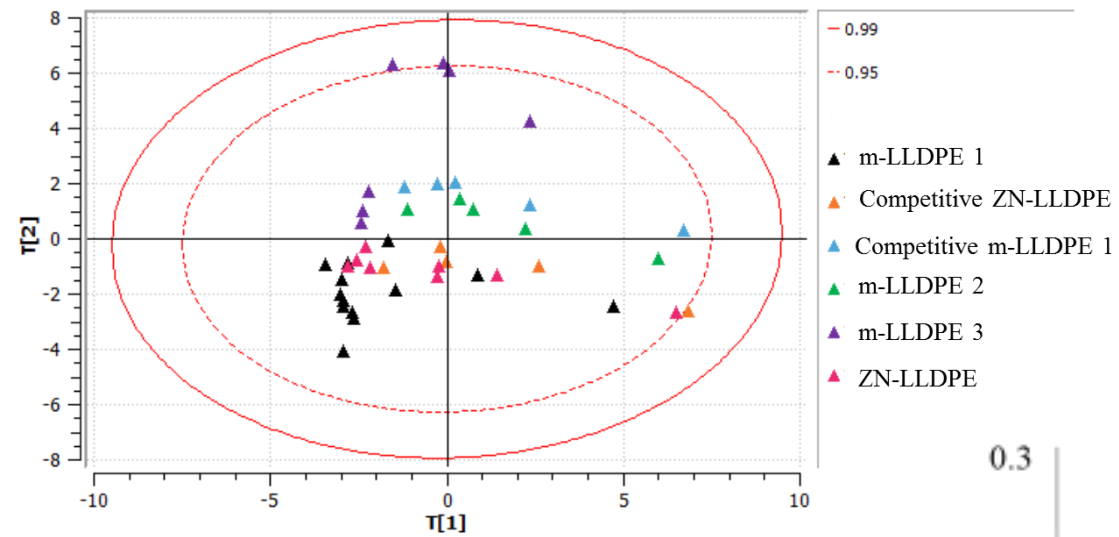
Use the Eigen values (λ_i) to determine the Eigen vectors(l_i): $[S - \lambda_i I] l_i = 0$

Technically, the Eigen vectors and values are determined iteratively using algorithms like NIPALS.

Blown Film Line Process Map



PCA for a Small Data Set



Test Methods

Test Description	Method	Based on
1% Secant Modulus	ExxonMobil Procedure	ASTM D882-95a
Tensile Test	ExxonMobil Procedure	ASTM D882-95a
Elmendorf Tear	ASTM D1922-15	
Dart Impact (Method A / B)	ExxonMobil Procedure	ASTM D1709-91
Puncture Test**	ExxonMobil Procedure	ASTM D 5748
Haze	ASTM D1003-13	
Gloss	ASTM D618	ASTM D2457-90
Average Gauge Mic*	ExxonMobil Procedure	ASTM D374
Resin Density	ASTM D1505-10	
Melt Index	ASTM D1238-13	
CFC Test	EM314-R4	
SAOS (Shear Rheology)	EM513-R2	
Rheotense (Extensional Rheology)	RHE04-3.3 & EM 514-R1	
TEM (General TEM Analysis)	EM-116 R2	

*Calibrated yearly.

**A steal probe is used instead of a Teflon coated probe.

DSC Analysis:

Samples of resin or film (3-5 mg) sealed in aluminum sample pans were heated and cooled in differential scanning calorimetry (DSC) at 10 °C/minute from -60 C to +220 C, from +220 C to -60 C and again from -60 C to +220 C with no hold time between each heating and cooling step. Each sample's heat of fusion (ΔH_f) was determined from its total heat flow (ΔH in J/g). Melting temperature was measured and reported during the second heating cycle (or second melt). Each sample's degrees of crystallinity was determined from its thermogram using the enthalpy of fusion of a perfect polyethylene crystal (ΔH_f°) of 4110 J/mole. Common heats of fusion (ΔH_f°) reported in the literature for a pure crystalline polyethylene ranges from 3977 J/mole to 4032 J/mole. The cumulative heat of fusion of each polyethylene was determined and the temperatures at 50%, 60%, 70% and 80% of the maximum cumulative heat of fusion noted.

General References on Analytical Methods

Cross explains linear rheology

$$\eta_{\gamma} = \eta_{\infty} + \frac{\eta_0 - \eta_{\infty}}{1 + k\gamma^n}$$

η_0 is zero shear viscosity

k is related to the relaxation time of the polymer in solution

γ is shear rate

n is the power law flow index

A. Yo. Malkin and A. I. Isayer, “Rheology: concepts, methods and Applications”, ChemTec Publishing, Canada, 200

GPC explains linear rheology using Double Reptation Theory

$$G'(\omega) = 2G_{No} \times \sum_{i=0}^N w_i \times \sum_{j=i}^N w_j \times \frac{Z_i^2}{1 + Z_i^2}$$

$$G''(\omega) = 2G_{No} \times \sum_{i=0}^N w_i \times \sum_{j=i}^N w_j \times \frac{Z_i}{1 + Z_i^2}$$

$$Z_i = \omega \tau_e (M_i / M_e)^{3.4}$$

J. D. Ferry, “Viscoelastic Properties of Polymers”, John Wiley & Sons, New York, 1980

- J. B. P. Soares and A. E. Hamielec, “Temperature rising elution fractionation of linear polyolefins”, Polymer Vol. 36 No. 8, pp. 1639-1654 (1995)
- J. B. P. Soares, “An Overview of Important Microstructural Distributions for Polyolefin Analysis”, Macromol. Symp., Vol. 257, pages 1–12 (2005)
- F. M. MIRABELLA, “Correlation of the Elution Behavior in Temperature Rising Elution Fractionation and Melting in the Solid-State and in the Presence of a Diluent of Polyethylene Copolymers”, Journal of Polymer Science: Part B: Polymer Physics, Vol. 39, 2819–2832 (2001)
- W. W. Yau, “Polyolefin Microstructure Characterization Using 3D-GPC-TREF”, 2005 PLACE Conference
- M. Vadlamudi, “Effect of Branching Architecture on the Crystallization Behavior of Random Ethylene Copolymers”, Ph. D. Dissertation Florida State University (2010).

General References on Statistical Methods

- D. C. Montgomery, “Design and Analysis of Experiments”, 3ed Edition, John Wiley & Sons, New York, 1991
- D. C. Montgomery, “Introduction to Statistical Quality Control”, 3ed, John Wiley & Sons, New York, DATE
- E. O. Thorp, “Elementary Probability”, John Wiley & Sons, Inc., New York, 1966
- E. Parzen, “Modern Probability Theory and Its Applications”, John Wiley & Sons, Inc., New York, 1992
- G. E. P. Box, W. G. Hunter, J. S. Hunter, “Statistics for Experimenters: An Introduction to Design, Data Analysis, and Model Building”, John Wiley & Sons, New York, 1978
- H. Cramer, “Mathematical Methods of Statistics”, 19th Ed., Princeton University Press, Princeton, 1999
- J. Neter, W. Wasserman, M. H. Kutner, “Applied Linear Regression Models”, 2nd Ed., Irwin, Homewood, Il, 1989
- L. H. C. Tipperr, “The Methods of Statistics”, John Wiley & Sons Inc., New York, 1952
- M. Hamburg, “Statistical Analysis for Decision Making”, 4th ed, Harcourt Brace Jovanovich, Publishers, New York, 1970
- T. Hastie, R. Tibshirani, J. Freidman, “The elements of Statistical Learning: Data Mining, Inference, and Prediction”, 2dn Edition, Springer, 2009
- W. J. Kennedy, Jr, and J. E. Gentle, “Statistical Computing”, Marcel Dekker, Inc., New York, 1980
- O. W. Davies, Editor, “Statistical Methods in Research and Production with Special Reference to the Chemical Industry”, Imperial Chemical Industries Limited, 1961

References on Multivariate Statistical Methods

- H. H. Harman, “Modern Factor Analysis”, 3ed revised, The University of Chicago Press, Chicago, 1976
- H van de Wasterbeemd, “Chemometric Methods in Molecular Design”, Weinheim, New York, 1995
- I.T. Jolliffe, “Principle Component Analysis”, Springer-Verlag, New York, 1986
- L. W. Johnson and R. D. Riess, “Introduction to Linear Algebra”, Additon-Wesley Publishing Company, Massachusetts, 1981
- L. Eriksson, E. Johansson, N. Kettaneh-Wold and S. Wold, “Introduction to Multi-and Megavariate Data Analysis using Projection Methods (PCA & PLS)”, Umetrics AB, 1999
- L. Eriksson, E. Johansson, N. Kettaneh-Wold and S. Wold,, “Multi-and Megavariate Data Analysis: Principles and Applications”, Umetrics AB, 2001
- M. A. Sharaf, D. L. Illman, B. R. Kowalski, “Chemometrics”, John Wiley & Sons, New York, 1986
- S. D. Conte, Carl de Boor, “Elementary Numerical Analysis”, 2dn Ed. , McGraw-Hill Book Company, New York, 1972
- A.Eslami, E. M. Qannari, A. Kohler, S. Bougeard, “Multivariate Analysis of Multiblock and Multigroup data”, Chemometrics and Intelligent Laboratory Systems, Vol., 133, pages 63-69 (2014)
- B.Skagerberg, J. F. MacGregor, C. Kiparissides, “Multivariate data analysis applied to low-density polyethylene reactors”, Chemometrics and Intelligent Laboratory Systems, Vol. 14, pages 341-356 (1992)
- Carl Duchesne, “Improvement of Process and Product Quality Through Multivariate Data Analysis”, Dissertation, McMaster University (2000)
- Carl Duchesne, John F. MacGregor “Defining Multivariate Specifications for Polyethylene Resins of ExxonMobil Chemical Company”, Baytown, Texas, (2001)
- Carl Duchesne, John F. MacGregor “Defining Multivariate Specifications for incoming raw materials”, Journal of Quality Technology, Vol. 36, No., 1 , pages 78-94 (2004)
- G. T. Duncan, “An Empirical Study of Jackknife-Constructed Confidence Regions in Nonlinear Regression”, Technometrics, Vol. 20, No. 2, pages 123-129 (1978)

- J. A. Westernuis, T. Kourti, J. F. MacGregor, “Analysis of Multiblock and Hierarchical PCS and PLS Models”, J. of Chemometrics, Vol. 12, pages 301-321 (1998)
- J. F. MacGregor, T. Kourti, “Multivariate Statistical Treatment of Historical Data for Productivity and Quality Improvements”,
- L. E. Wangen, B. R. Kowalski, “A Multiblock Partial Least Squares Algorithm for Investigating Complex Chemical Systems”, J. of Chemometrics, Vol. 3, pages 3-20 (1988)
- P. Geladi, “Analysis of Multi-way (Multi-Mode) Data”, Chemometrics and Intelligent Laboratory Systems, Vol. 7, pages 11-30 (1989)
- P. Nomikos, J. F. MacGregor, “Multi-way partial least squares in monitoring batch processes”, Chemometrics and Intelligent Laboratory Systems, Vol. 30, pages 97-108 (1995)
- P. R. C. Nelson, P. A. Taylor, J. F. MacGregor, “Missing data methods in PCS and PLS: Score calculations with incomplete observations”, Chemometrics and Intelligent Laboratory Systems Vol. 35 pages 45-65 (1996)
- S. Wold, N. Kettaneh-Wold, B. Skagerberg, “Nonlinear PLS Modeling”, Chemometrics and Intelligent Laboratory Systems, Vol. 7, pages 53-56 (1989)
- S. Wold, “The Analysis of Multivariate Chemical Data using SIMCA and MACUP”, Kemia-Kemi, Vol. 6, pages 401-405 (1982)
- S. Wold, C. Albano, W. J. Dunn III, K. Esbensen, S. Hellberg, E. Johansson, W. Lindberf and M. Sjostrom, “Modeling data tables by principal components and PLS : class patterns and quantitative predictive relations”, Analusis, Vol. 12, No. 10, pages 477-485 (1984)
- J. F. MacGregor, T. Kourti, “Multivariate Statistical Treatment of Historical Data for Productivity and Quality Improvements”,

- D. F. Morrison, “Multivariate Statistical Methods”, McGraw-Hill Book Company, New York, 1976
- J. E. Jackson, “A User’s Guide to Principle Components”, John Wiley & Sons, Inc. New York, 1991
- R. A. Johnson, D. W. Wichern, “Applied Multivariate Statistical Analysis”, Pearson Prentice Hall, NJ, 2007
- S. Wold, “Principal Component Analysis”, Chemometrics and Intelligent Laboratory Systems, Vol. 2, pages 37-52 (1987)
- S. Wold, N. Kettaneh, K. Tjessem, “Hierarchical Multiblock PLS and PC Models for Easier Model Interpretation and as an Alternative to Variable Selection”, J. of Chemometrics, Vol. 10, pages 463-482 (1996)