



From Data-Driven Models to Material Characterization: A New Approach to Improve Durability and Mechanical Performance of High-Early Strength Concretes

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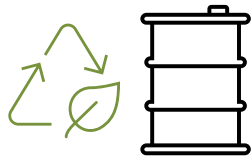


Decarbonization strategies in the cement and concrete industries

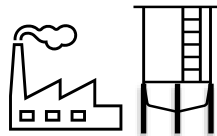
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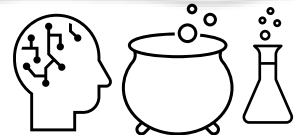
Readily implementable solutions:



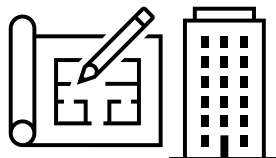
Efficiency of clinker production



Efficiency of cement production



Efficiency of concrete proportioning



Efficiency of structural design

Our Research focus



Long-term solutions:



Electrification of cement production



Alternative cements



Carbon sequestration

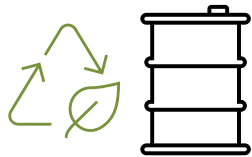


Decarbonization strategies in the cement and concrete industries

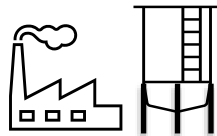
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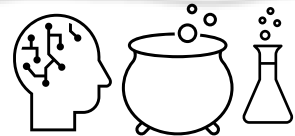
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Efficiency of clinker production

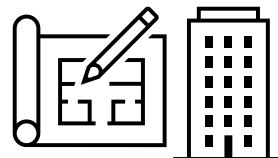


Efficiency of cement production



Efficiency of concrete proportioning

Focus of this presentation



Efficiency of structural design

*Sunday, April 2nd
3:30 – 5:30 PM,
Yosemite A*



Long-term solutions:



Electrification of cement production



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Carbon sequestration



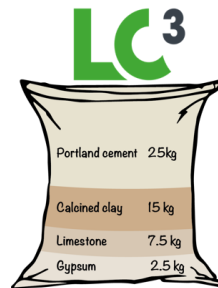
Motivation of this Study

New green materials emerge everyday...

Electrically produced cement

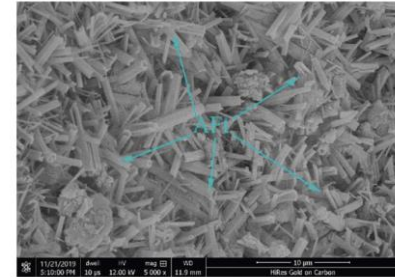


<http://sublime-systems.com/>



<http://lc3.ch/about-lc3/>

CSA cements



<https://www.hindawi.com/journals/amse/2021/4494056/>

Challenges:

- Extensive studies to assess all performance needs
- Unknown long-term performance
- Limited data available for complex AI modeling

Enzymatic self-healing cementitious material



<https://cen.acs.org/materials/Enzymes-power-carbon-sucking-alternative/100/i6>

Credit: Shuai Wang, Suzanne Scarlata, Nima Rahbar

Problem Statement

Major Need:

Efficient tools to **expedite the incorporation of new materials** into new and existing concrete formulations



Mixture Design
-> Optimization <-

Tradeoff [performance – cost – emissions]



-> Overall visualization <-

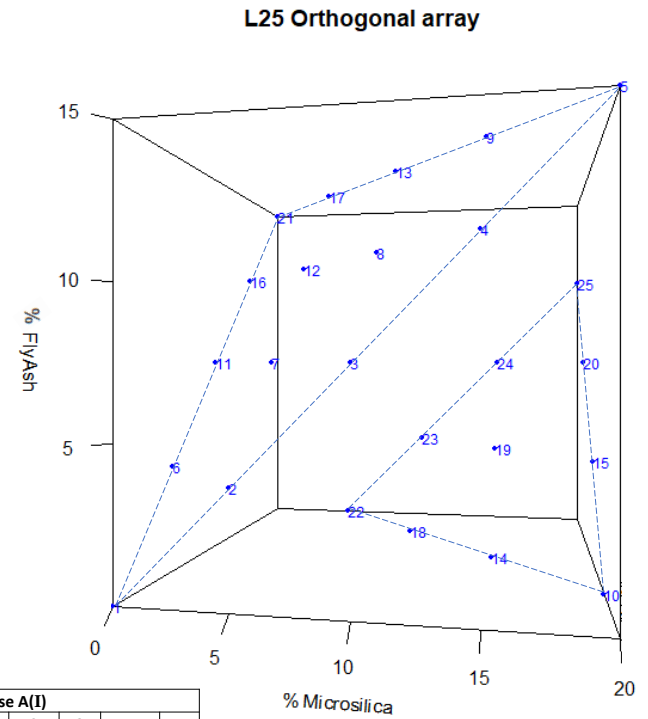
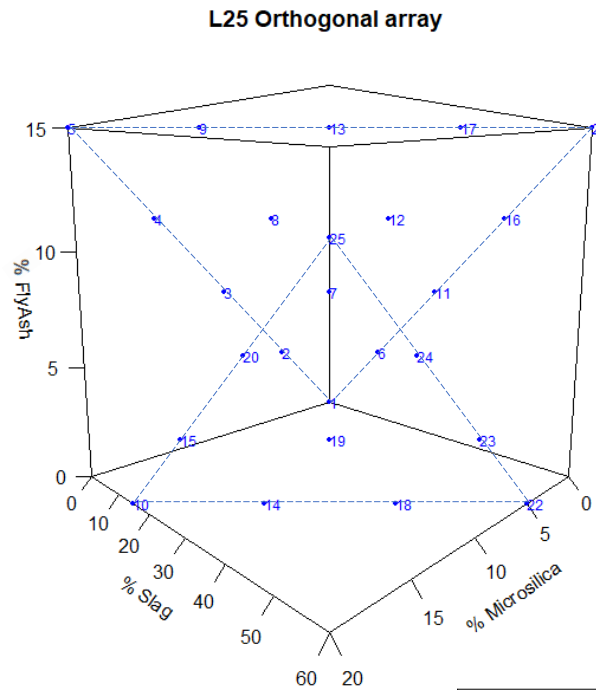
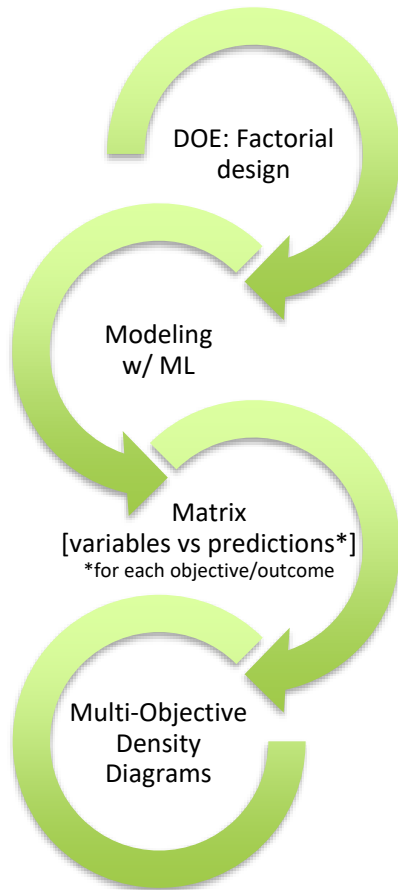
Key questions addressed in this research

1. Can we effectively optimize concrete mix design w/ **few experimental runs**?
2. Can we evaluate: mechanical performance $\leftarrow f(\text{changes in mix proportion})$ in an easy and intuitive way?



Optimization strategy

Conceptual framework



		Phase A(I)				
Levels		1	2	3	4	5
Features	Slag	0	15	30	45	60
	Microsilica	0	5	10	15	20
	Fly Ash	0	3.75	7.5	11.25	15

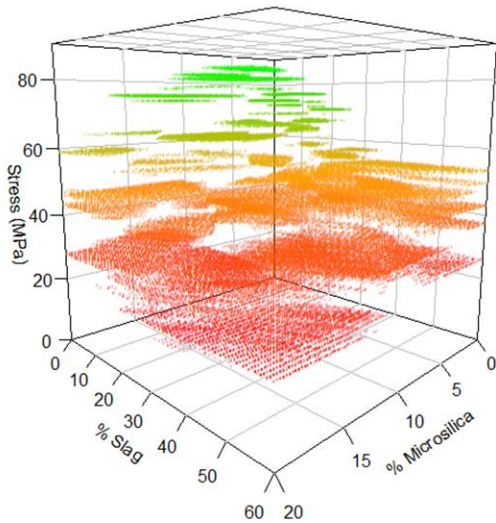
Modeling

Methods/algorithms:

- kNN
- Random Forest

Modeling

Fly Ash = 3.5 %



Predicted compressive strength (MPa)

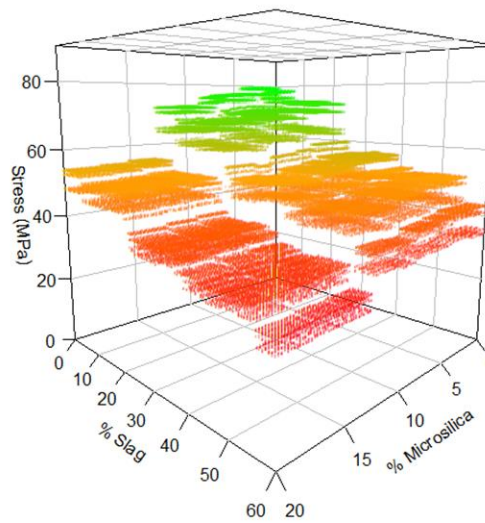


20 30 40 50 60 70 80

kNN Model

+

Fly Ash = 3.5 %



Predicted compressive strength (MPa)

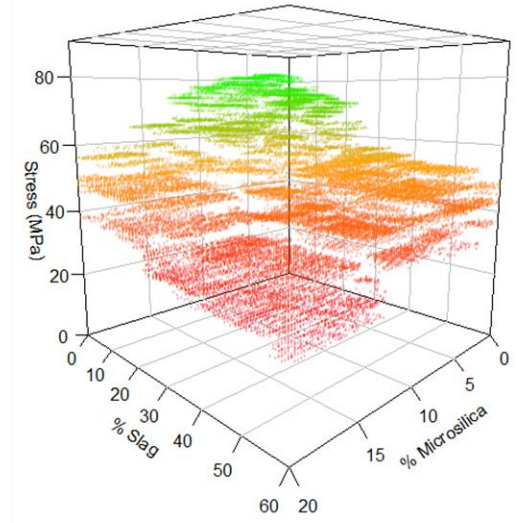


30 40 50 60 70

RF Model

=

Fly Ash = 3.5 %



Predicted compressive strength (MPa)



30 40 50 60 70 80

Ensemble Model



Optimization case studies

Objective

Find optimum binder formulations for:

- *3D printing application*
- *Self-consolidating precast HPC*

Experimental campaign

Fresh and hardened properties measured:

- *Compressive strength (2h, 4h, 6h, 1d, 7d, 28d)*
- *Static flow (self-consolidating)*
- *Dynamic flow (add energy)*
- *Initial and final setting times*
- *Free shrinkage*

Design of Experiment (36 mixtures)

Variables:

- *Calcium-aluminate based mineral admixture [10 - 32]%*
- *High-range water reducer to cementitious ratio (HRWR/cm) [0 - 1.25]%*
- *Water-to-cementitious ratio (w/cm) [0.20 - 0.45]*

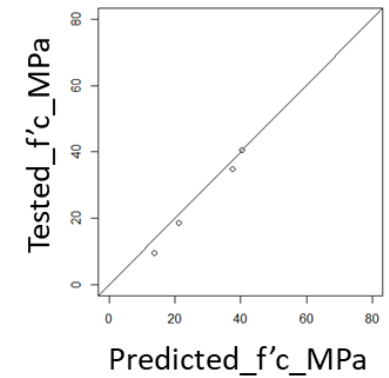
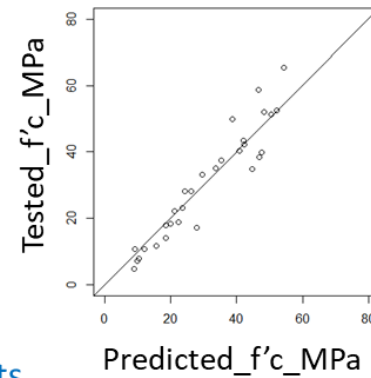
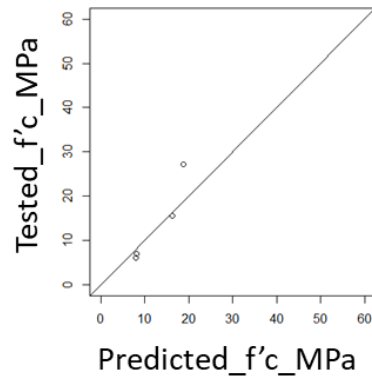
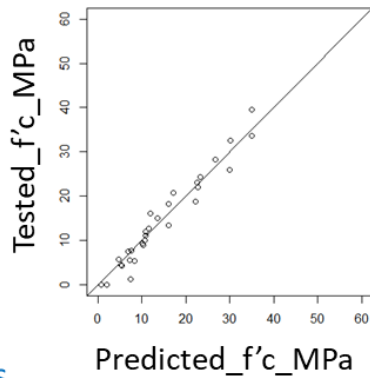
Estimating compressive strength

TRAIN SET

TEST SET

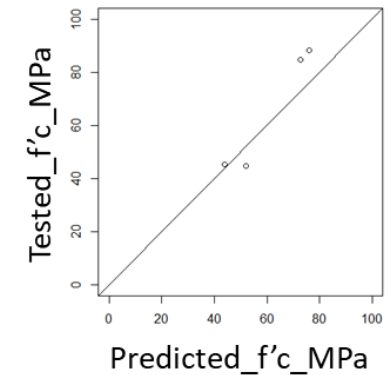
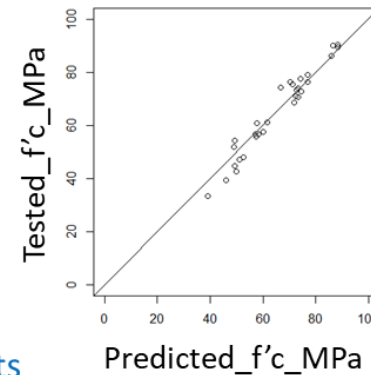
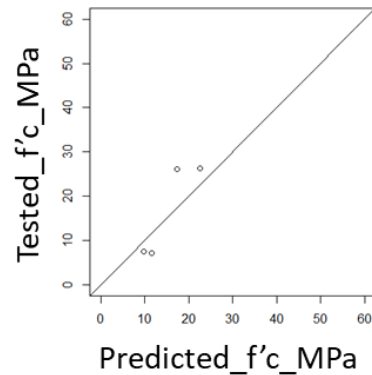
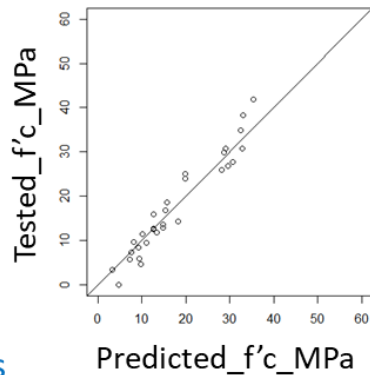
TRAIN SET

TEST SET



2h tests

1d tests

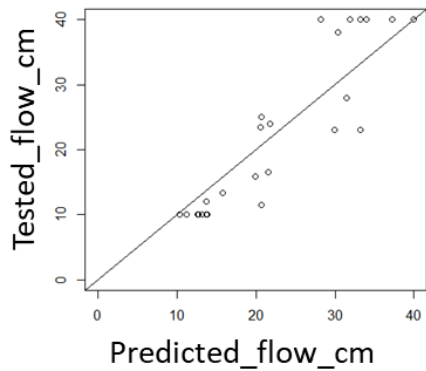


4h tests

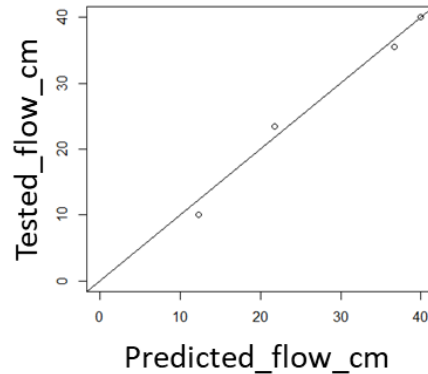
7d tests

Estimating static and dynamic flow

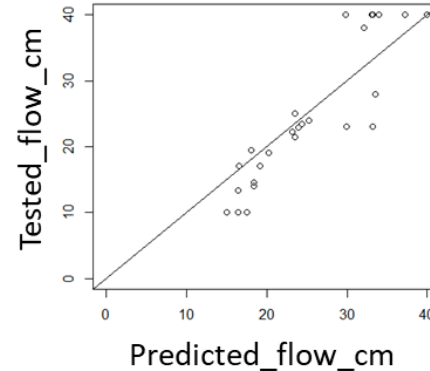
TRAIN SET



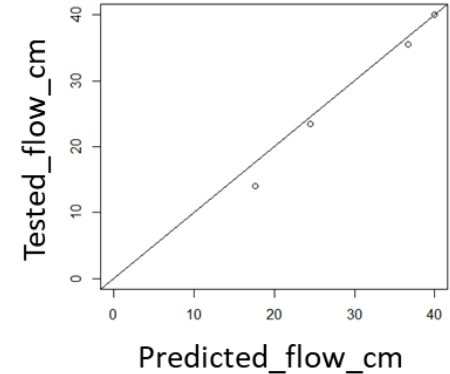
TEST SET



TRAIN SET



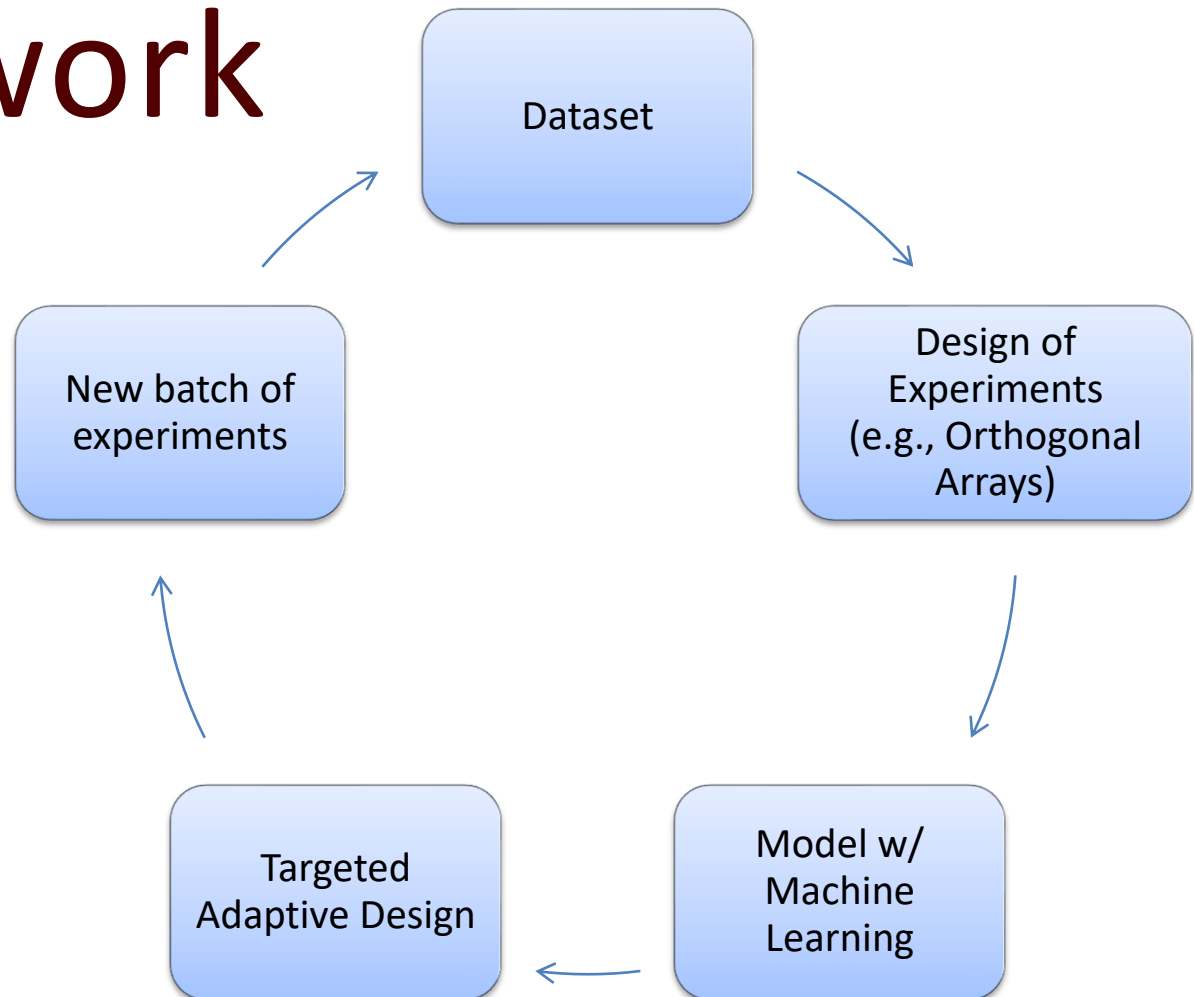
TEST SET



SC_flow

TD_flow

Future work



Key questions addressed in this research

- ✓ 1. Can we effectively optimize concrete mix design w/
few experimental runs?



Mixture Design
-> Optimization <-

C. Tavares, X. Wang, S. Saha, Z. Grasley, *Machine Learning-Based Mix Design Tools to Minimize Carbon Footprint and Cost of UHPC. Part 1: Efficient Data Collection and Modeling*, Cleaner Materials (2022), doi:
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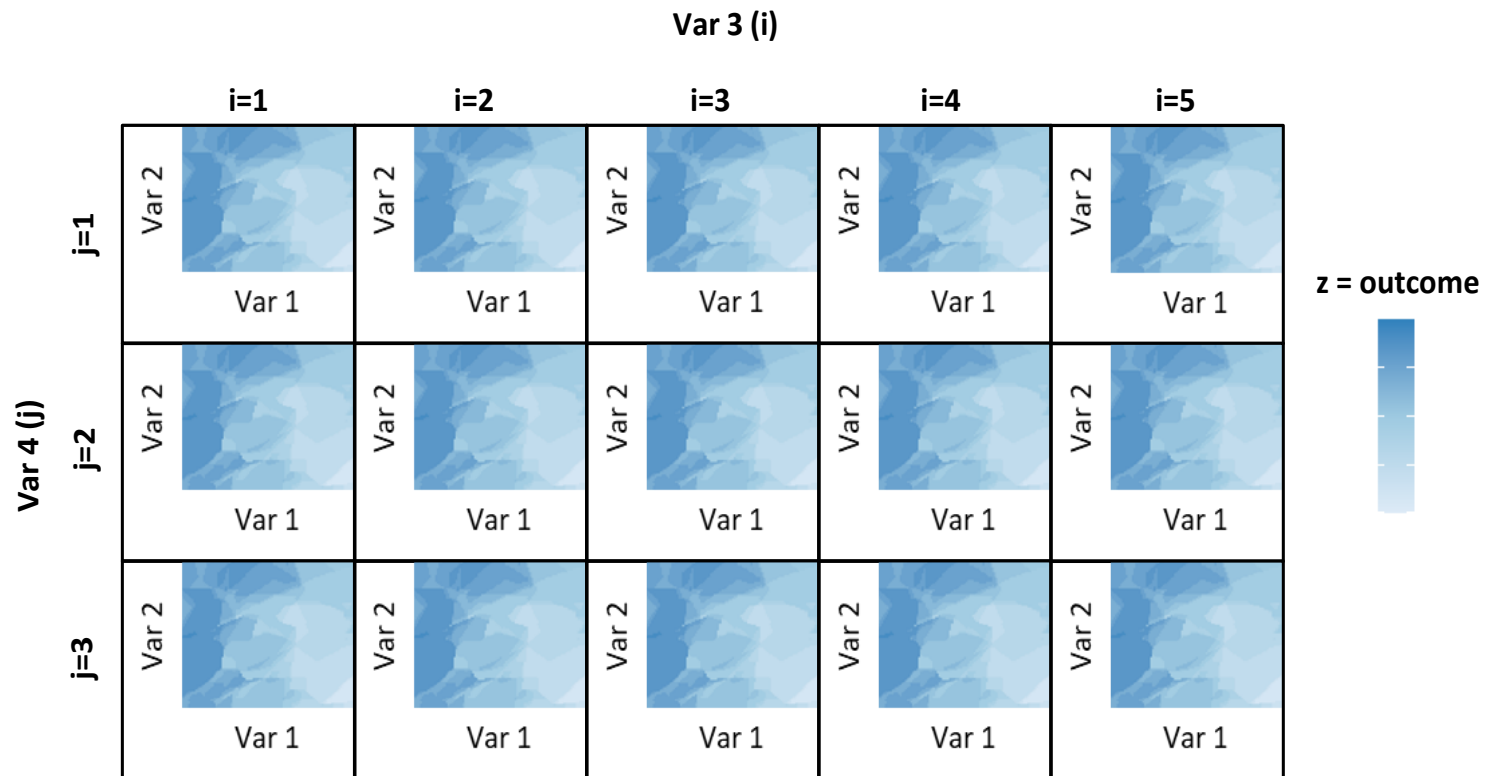
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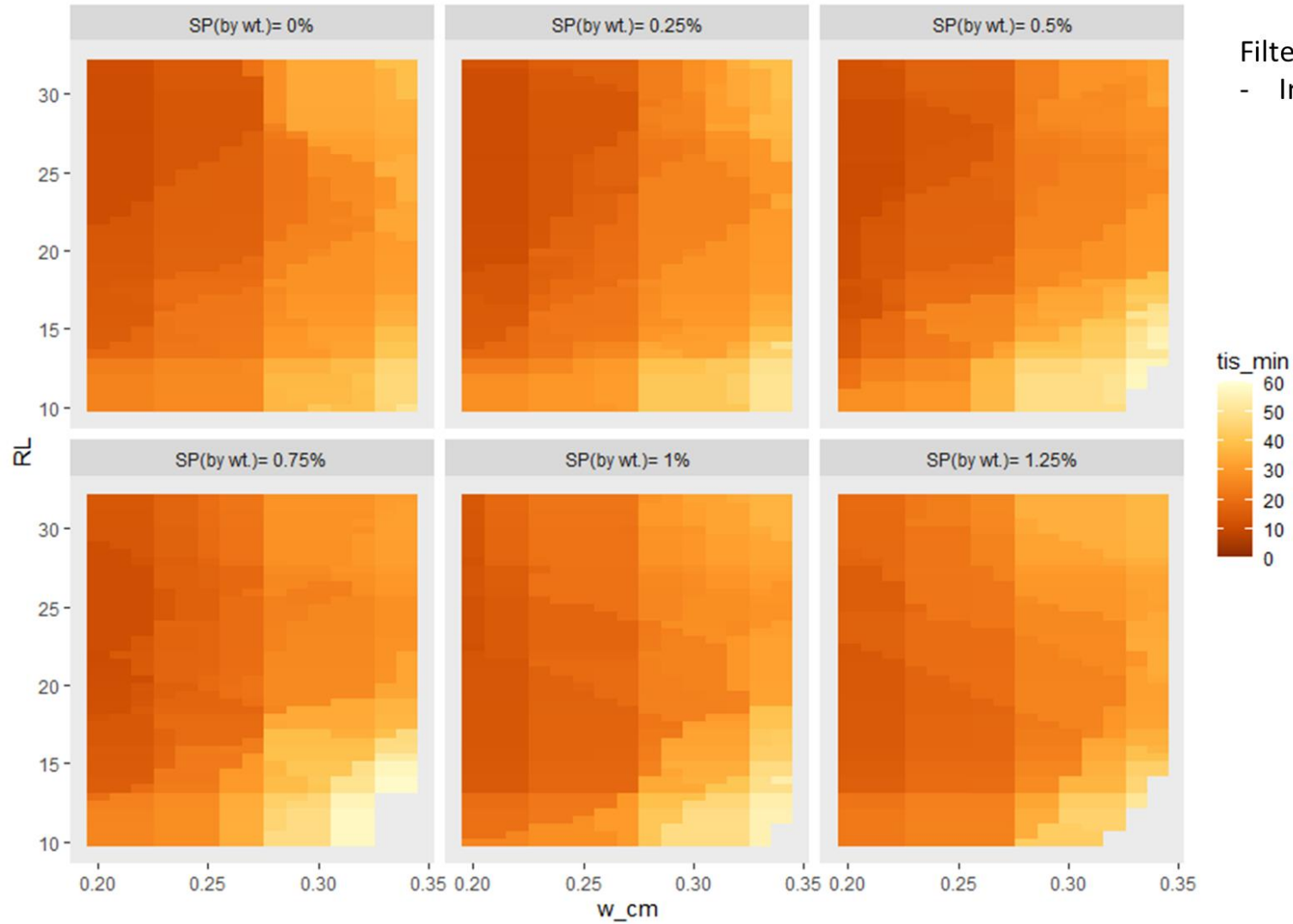
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2. Can we evaluate: mechanical performance \leftarrow f(changes in mix proportion) in an **easy and intuitive way**?



Performance Density Diagrams

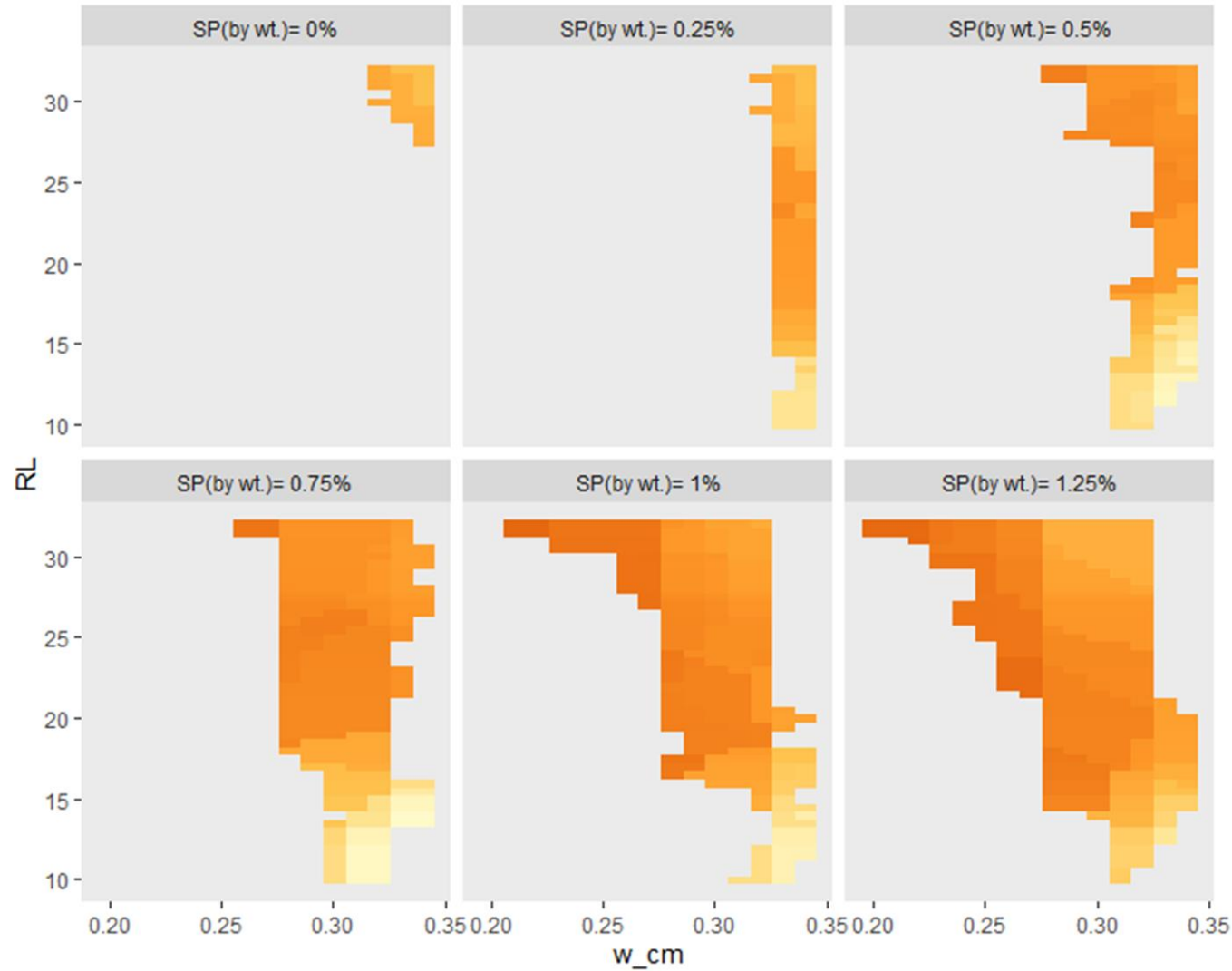
PDD





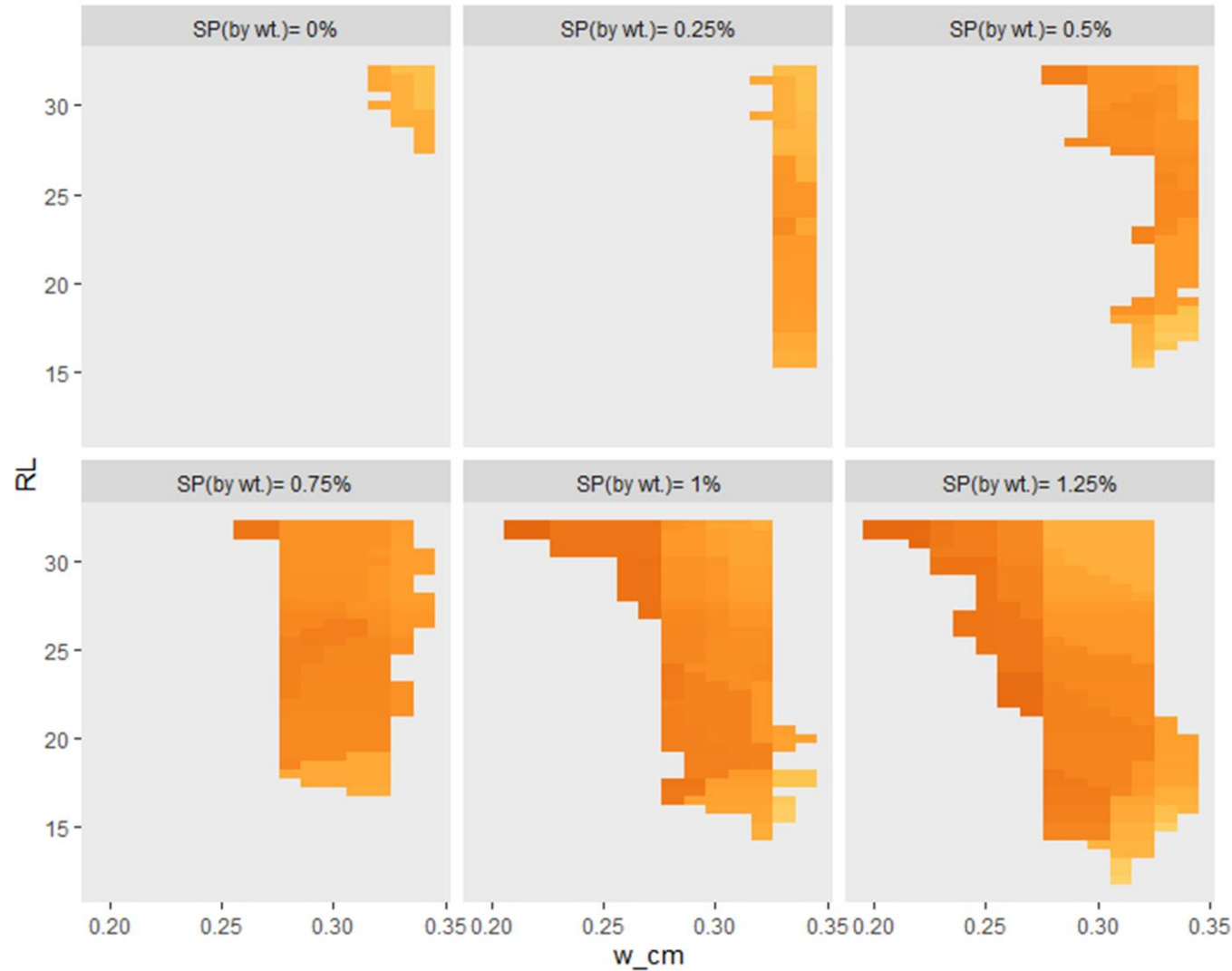
Filters:

- Initial setting time < 60mins



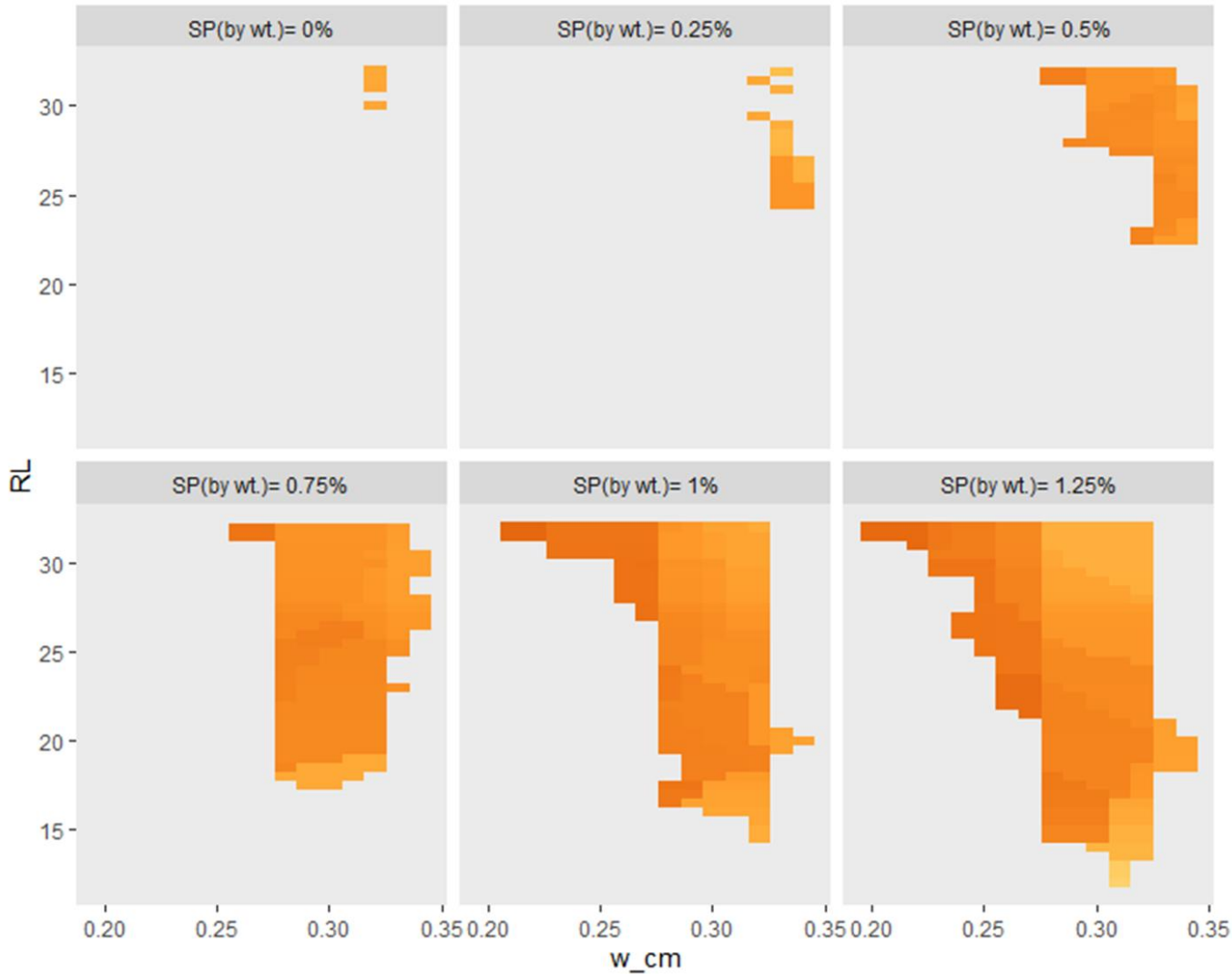
Filters:

- Initial setting time < 60mins
- SC flow = [22-34]cm



Filters:

- Initial setting time < 60mins
- SC flow = [22-34]cm
- fc_2h > 10 MPa (1450 psi)



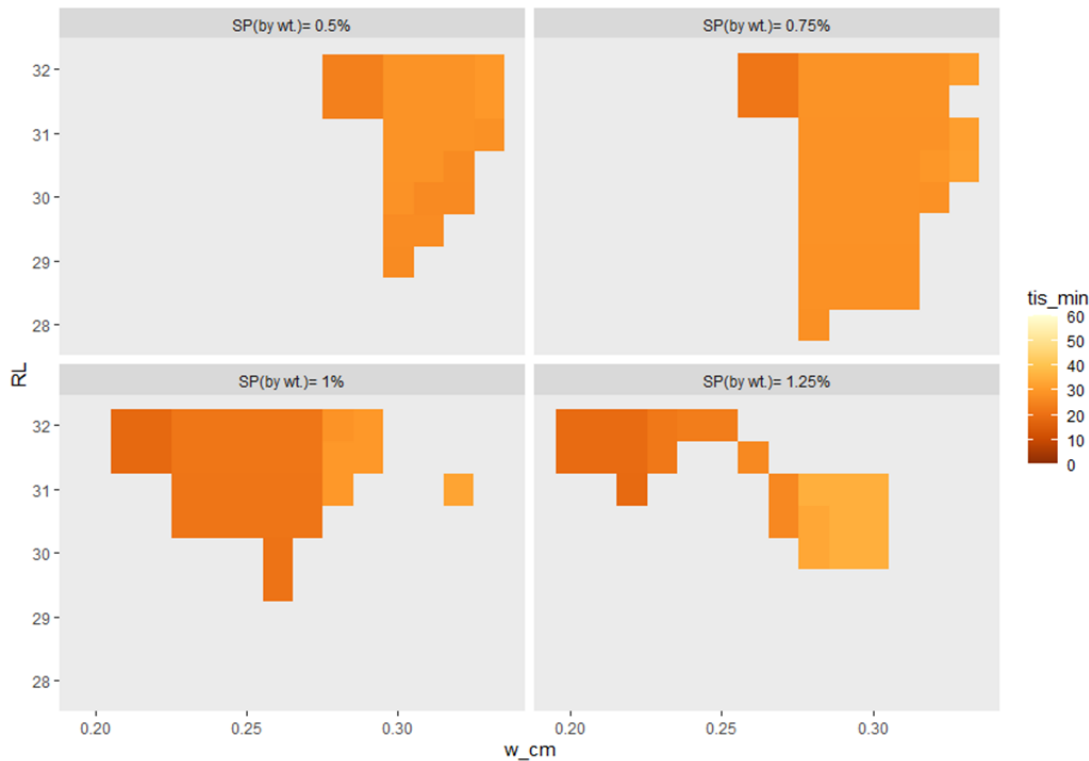
Filters:

- Initial setting time < 60mins
- SC flow = [22-34]cm
- $f_{c_2h} > 10$ MPa (1450 psi)
- $f_{c_6h} > 20$ MPa (2900 psi)



Filters:

- Initial setting time < 60mins
- SC flow = [22-34]cm
- $f_{c_2h} > 10$ MPa (1450 psi)
- $f_{c_6h} > 20$ MPa (2900 psi)
- $f_{c_1d} > 30$ MPa (4400 psi)
- $f_{c_7d} > 50$ MPa (7250 psi)
- $f_{c_28d} > 60$ MPa (8800 psi)
- Free shrinkage < $(-1600)\mu\epsilon$



Self-consolidating precast HPC

Design Filters:

- Initial setting time < 60mins
- SC flow = [25-34]cm
- $w/cm < 0.29$
- $fc_{2h} > 22$ MPa (3,200 psi)
- $fc_{4h} > 24$ MPa (3,500 psi)
- $fc_{6h} > 30$ MPa (4,350 psi)
- $fc_{1d} > 44$ MPa (6,400 psi)
- $fc_{7d} > 80$ MPa (11,600 psi)
- $fc_{28d} > 90$ MPa (13,000 psi)

Mix	RL	w_cm	HRWR_cm
O-SCC-1	21	0.28	1.2

Very high risk of cracking

Design Filters:

- Initial setting time < 60mins
- SC flow = [25-34]cm
- $w/cm < 0.27$
- $fc_{2h} > 22$ MPa (3,200 psi)
- $fc_{4h} > 26$ MPa (3,700 psi)
- $fc_{6h} > 28$ MPa (4,060 psi)
- $fc_{1d} > 45$ MPa (6,525 psi)
- $fc_{7d} > 65$ MPa (9,425 psi)
- $fc_{28d} > 70$ MPa (10,150 psi)

Mix	RL	w_cm	HRWR_cm
O-SCC-2	30	0.26	1%

low risk of cracking

3D printing binder

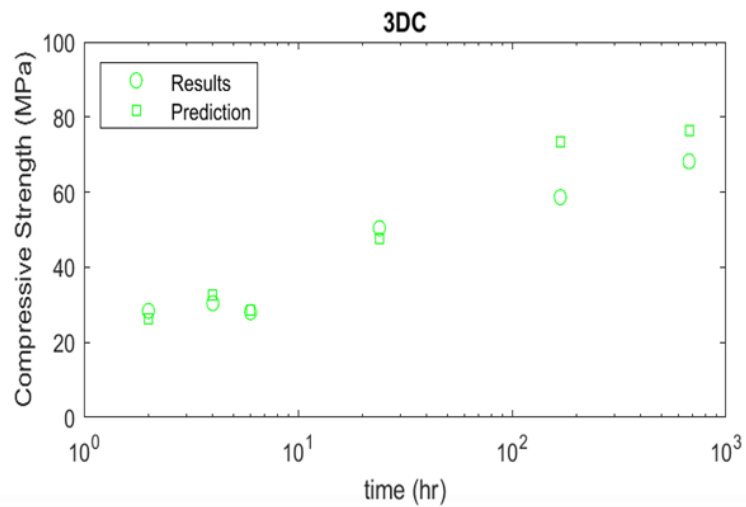
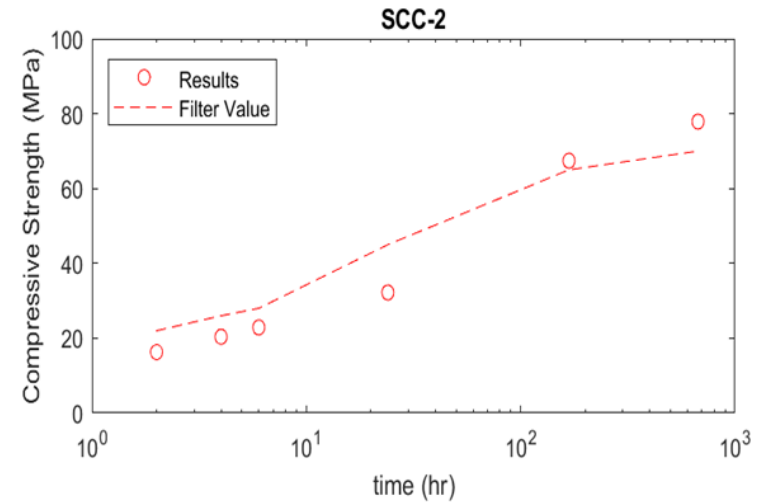
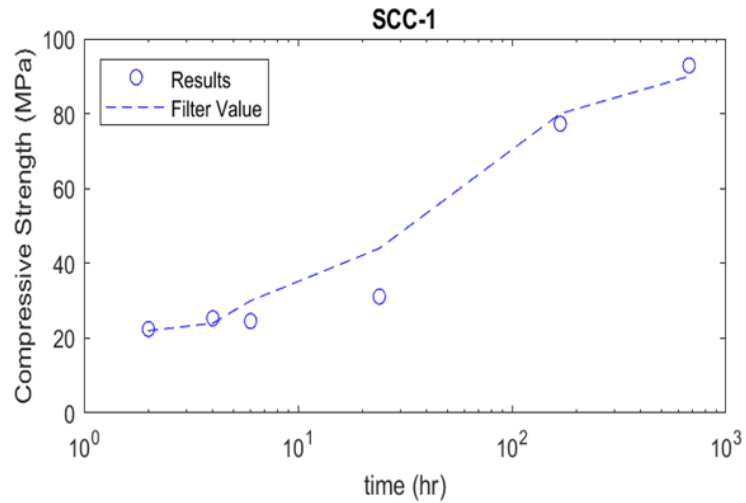
Mix	RL	w_cm	HRWR_cm
O-3D	25	0.22	0.35

low risk of cracking

Design Filters:

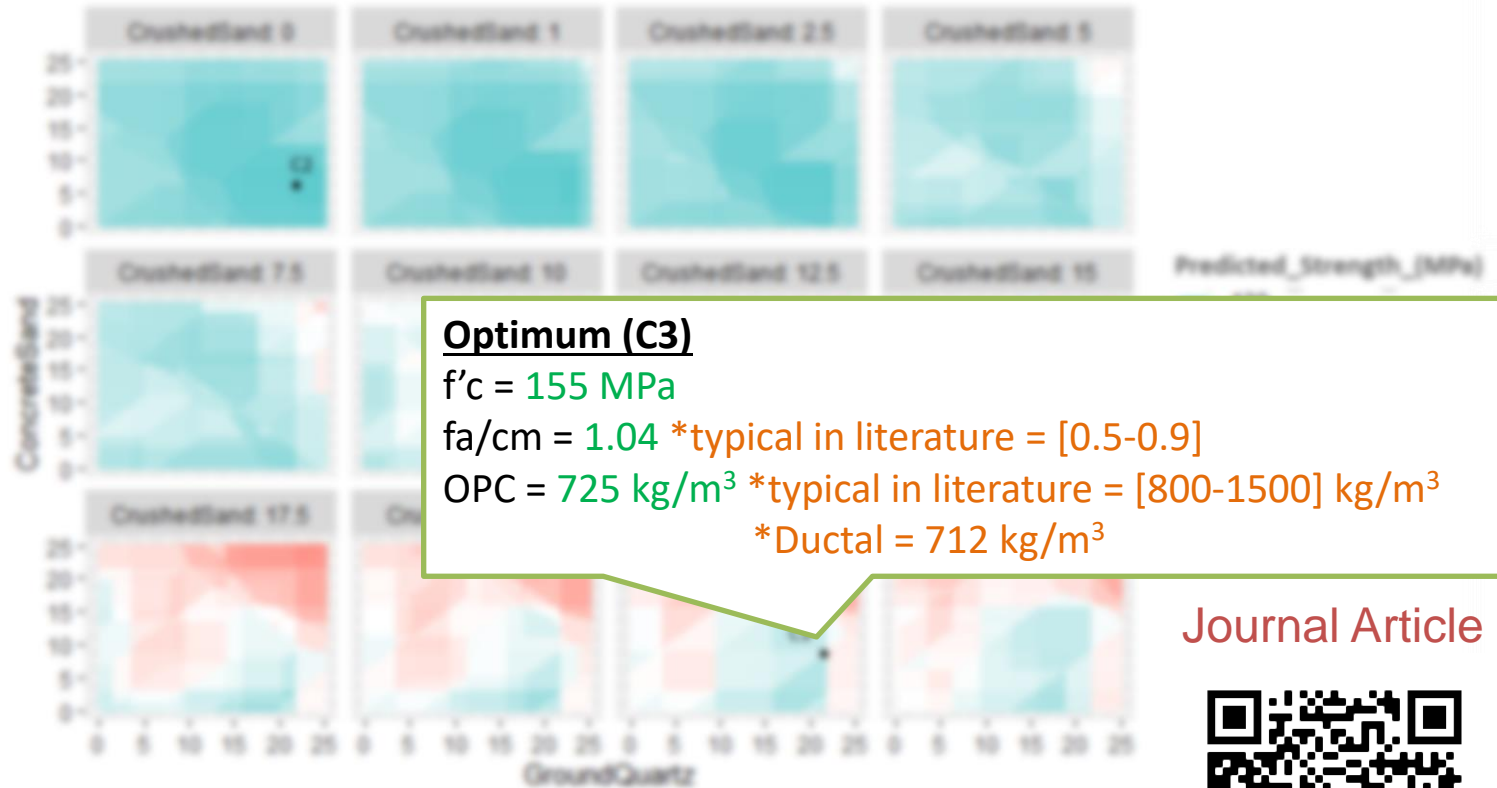
- Initial setting time < 60mins
- HRWR/cm \leq 0.5%
- w/cm < 0.26
- RL \leq 25%
- SC flow < 11 cm
- TD flow > 13 cm
- f_{c_2h} > 20 MPa (2,900 psi)
- f_{c_1d} > 35 MPa (5,075 psi)

Predictions vs Strength



PDD

UHPC



Optimum (C3)

$f'c = 155 \text{ MPa}$

$fa/cm = 1.04$ *typical in literature = [0.5-0.9]

OPC = 725 kg/m^3 *typical in literature = [800-1500] kg/m^3

*Ductal = 712 kg/m^3

Journal Article



Mixture #	SCM replacing cement (% by wt)			Aggregates replacing conventional (% by wt)			28 day results	
	Silica	Microsilica	Fly Ash	Ground Quartz	Concrete Sand	Crushed Sand	$f'c$ (MPa)	f_t (MPa)
C1	0	10.1	0	22	6.5	0	128.4	111.8
C2	22.4	5.25	1.97	22	6.5	0	129.2	116.1
C3	22.4	5.25	1.97	21.5	6.5	22	128.5	114.8

Key questions addressed in this research

- ✓ 1. Can we effectively optimize concrete mix design w/ few experimental runs?
- ✓ 2. Can we evaluate: mechanical performance \leftarrow f(changes in mix proportion) in an **easy and intuitive way**?

Tradeoff [performance – cost – emissions]



-> Overall visualization \leftarrow

CONCLUSIONS

- ✓ 1. Can we effectively optimize concrete mix design w/ few experimental runs? -> **YES (OA+ML)**
- ✓ 2. Can we evaluate the effect of changes in mix proportioning on mechanical performance in an easy and intuitive way? -> **YES (PDD)**



Related Publications

Related Publications

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Related Publications

E Tavares, Cesario Sarmiento, Goncalves Martins. (2022). *Multi-objective density diagrams developed with machine learning models to optimize sustainability and cost-efficiency of UHPC mix design* (Order No. 30372235). Available from Dissertations & Theses @ Texas A&M; Dissertations & Theses @ Texas A&M System; ProQuest Dissertations & Theses Global. (2784742994). Retrieved from <http://proxy.library.tamu.edu/login?url=https://www.proquest.com/dissertations-theses/multi-objective-density-diagrams-developed-with/docview/2784742994/se-2>



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THANK YOU!

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