

## SAS GLOBAL EORUN nnnn

## MARCH 29 - APRIL 1 WASHINGTON, DC

SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. <sup>®</sup> indicates USA registration. Other brand and product names are trademarks of their respective companies.



#### TAP TO GO BACK TO KIOSK MENU







#### Abstract

Introduction Methods Results 1 Results 2 Conclusion

In 2018, natural gas was the largest source of energy production in the United States, accounting for 31.8% of all energy production. Midstream companies are responsible for transportation and processing of natural gas. One of the biggest problems facing midstream companies is meter freezing. A meter freeze is caused by the presence of natural gas hydrates (a high-pressure form of frozen water and natural gas molecules) in the tap valves, gauge lines, or manifold so that the differential sensing element is effectively no longer connected to the flow line. Because one side of the manifold is likely to freeze before the other, small changes in line pressure on either side of the orifice can create large changes in the indicated differential pressure record. The differential may read either high or low as a result of meter freeze, and the effect may cause substantial measurement error.

Currently, data analysts spend hundreds of man-hours looking through data for possible meter freezes, and this manual process is time-consuming, tedious, and error-prone. Thus, the goal of our project is to use advanced machine learning models in SAS and Python to identify meter freezes. In SAS Enterprise Miner we used Logistic Regression, Neural Network, Decision Tree, Gradient Boosting, and the HP Forest nodes. With Python scikitlearn library we ran Logistic Regression, Random Forest, Decision Tree, Ensemble, and XG Boost Models. SAS Enterprise Miner Gradient Boosted Model outperformed the rest based on the overall F1 score.

The best model is able to correctly classify meter freezes, and it is saving a midstream company millions of dollars in revenue and man-hours.

### PREDICT FREEZES IN NATRUAL GAS PIPELINES

Bingi Arnold Kanagwa M.S, Ho -Chang Chae, PHD

University of Central Oklahoma



#### TAP TO GO BACK TO **KIOSK MENU**

## PREDICT FREEZES IN NATURAL GAS PIPLELINES

INIVERSITY OF Central Oklahoma

#### Natural Gas Pipelines and Meter Freezes

- production in 2018
- natural gas
- Total well head value of \$85.3 billion
- gas companies.

  - connected to the flow line.

#### Objective

- Improve accuracy by reducing human error
- Save time and money

#### Abstract

#### Introduction

Methods

Results 1

Results 2

Conclusion

Bingi Arnold Kanagwa M.S, Ho Chang Chae, PHD

University of Central Oklahoma

Natural gas in the United States was the nations largest source of energy

This represents 31.8% of all energy production in the country In 2018, the United States produced 32.7 trillion cubic feet of marketed

Average well head values is \$2.66 per thousand cubic feet Meter freezes are one of the biggest sources of lost revenue for natural

Meter freezes are caused by the presence of natural gas hydrates (a high pressure form of frozen water and natural gas molecules) in

the tap valves, gage lines, or manifold.

Then, the differential sensing element is effectively no longer

Meter freezes cause substantial measurement error which leads to tens of millions of dollars in lost revenue for midstream companies

• Build machine learning models to quickly identify freezes



Illustration of a meter freeze





	Sing freeze
Abstract Introduction	AL_FREEZ Data Partition
Methods	
Results 1	
Results 2	Transform Variables
Conclusion	

Extreme Gradient Boosted (selected model)

## PREDICT FREEZES IN NATURAL GAS PIPLELINES

#### Bingi Arnold Kanagwa M.S, Ho Chang Chae, PHD

#### University of Central Oklahoma



#### Scikit-learn

- Logistic Regression
  - Random Forrest
    - Decision Tree
  - Ensemble Model

```
#model with no transformations
def my_model_nt (data ):
   data_2=data.set_index('Date')
   data_3=data_2.dropna()
   data_4=data_3.drop(['Number','Name'],axis=1)
   predictions=xgb_clf.predict(data_4)
   probabilities=xgb_clf.predict_proba(data_4)
   score=probabilities[:,1]
   data_3['predictions']=predictions
   data_3['<mark>score</mark>']=score
   data_6=data_3[data_3['predictions']==1]
   data_7=data_6.drop(['Differential','Pressure','Temperature','Flow Duratic
   data_7.to_csv('arnold_freeze_xgb.csv')
   return(data_7)
```

#### SAS Enterprise Miner

- Decision Tree
- Logistic Regression
- Neural Network
- Gradient boosted (selected model )





		SAS E	interpris	e miner
	Model Description	precision	recall	F1 score
Abetroet	Decision Tree	0.8750	0.8077	0.84
ADSIIAUI	Regression	0.6875	0.4231	0.523809524
Introduction	Neural Network	0.8214	0.8846	0.851851852
Methods	HP Forest	0.8800	0 8462	0.862745098
Doculto 1	Gradient boosting	0.8846	0.8846	0.884615385
NESUIIS I				
Results 2				
Conclusion				

#### Scikit-learn

- based on F1 score.

#### SAS Enterprise Miner vs. Scikit-learn

Scikit-learn

## PREDICT FREEZES IN NATURAL GAS PIPLELINES

Bingi Arnold Kanagwa M.S, Ho Chang Chae, PHD

University of Central Oklahoma

#### SAS Enterprise Miner

- Precision (accuracy of positive results) lacksquare
- Recall (ratio of positive instances correctly detected by the classifier) ullet
- F1 score is a combination of the two measures  $\bullet$
- Gradient Boosted model performed the best

Random Forest model had the best precision Gradient Boosted model had the best over-all score

Model Descriptio Decision Tree Regression Random Forest Gradient boostin Ensemble

1. Overall, models created with SAS Enterprise Miner performed better than models developed using

		Sci-kit le	arn
on	precision	recall	F1 score
	0.6296	0.7083	0.666635294
	0.7142	0.625	0.666629331
	0.8947	0.7083	0.79066252
ıg	0.8333	0.8333	0.8333
	0.8888	0.6666	0.761828571





#### Scoring and Implementing Selected Model

Abstract Introduction Methods Results 1 Results 2 Conclusion

- Results from gradient boosted model was used to identify ulletfreezes
- Machine learning significantly reduced the amount of time ullettaken to classify freezes
- Less than 3 seconds to classify over 13000 meters  $\bullet$
- Human analysts would require at least three work days. lacksquare

Number	Name	score
3931	HUDGINS #17-2	0.5502276
3931	HUDGINS #17-2	0.6271132
3951	SCHOU #1-21	0.68662345
105340	BOLES FIELD CHECK	0.63042957
110464	HUTCHINSON 27 H #1	0.66404
110464	HUTCHINSON 27 H #1	0.91817516
110464	HUTCHINSON 27 H #1	0.5946889
20018	ROOS 33-8	0.9836052
20411	HAMMETT 32-1 ALT	0.97913504
208373	B S HARRISON	0.7180905
208373	B S HARRISON	0.545215
208382	WEATHERFORD CP	0.8604461
208449	ETHANE RESIDUE	0.68537647
208449	ETHANE RESIDUE	0.66393965
	Number 3931 3931 3951 105340 110464 110464 110464 20818 20818 208373 208373 208373 208382 208449	Number         Name           3931         HUDGINS #17-2           3931         HUDGINS #17-2           3951         SCHOU #1-21           105340         BOLES FIELD CHECK           110464         HUTCHINSON 27 H #1           20018         ROOS 33-8           20411         HAMMETT 32-1 ALT           208373         B S HARRISON           208373         B S HARRISON           208382         WEATHERFORD CP           208449         ETHANE RESIDUE           208449         ETHANE RESIDUE

## PREDICT FREEZES IN NATURAL GAS PIPLELINES

#### Bingi Arnold Kanagwa M.S, Ho Chang Chae, PHD

University of Central Oklahoma

0	20018	[ROO	S 33-8]
<u>D</u> at	ta <u>R</u> e	port <u>!</u>	<u>S</u> et-Up
Sy:	stem	ENTE	RPRISE
Na	me	ROO:	5 33-8
• F	low D	ata	O Ch
Fel	oruan	Y	• 202
FLO	Peri	odic	Daily
WCA.	Date	e//	
EX	02/0	01/20	20 09:0
olore	02/0	02/20	20 09:0
-	02/0	03/20	20 09:0
	02/0	04/20	20 09:0
	02/0	05/20	20 09:0
	02/0	06/20	20 09:0
	02/0	07/20	20 09:0
	and the second se		

February, 2020		
<u>Options View Help</u>		
• Meter • 🛃 20018	· È::	
aracteristic 💿 Analysis 💿 Equipment 💿 Components		
Open Auto		
Monthly		

	EX Count	Differential	Pressure	Temperature	Extension	<b>Relative Density</b>	Flow Time	Volume	Ene
0:00	0	2.341	451.15	53.58	32,4452	0.62070	018:18:25	158.248	3
0:00	0	3.396	455.51	い 57.57	37.7769	0.62070	022:49:49	215.650	1
0:00	0	1.839	455.04	59.81	28.9905	0.62070	022:23:19	172.373	
0:00	0	1.922	446.05	59.05	29.1529	0.62070	022:08:53	169.805	3
0:00	0	3.622	441.28	50.34	36.4042	0.62070	018:35:33	171.898	12
0:00	0	287.855	310.76	30.58	298.7134	0.62070	009:13:40	608.110	6
0:00	9	5.001	446.76	52.56	46.4606	0.62070	018:50:41	226,468	3
0:00	0	2.330	448.68	55.67	31.9572	0.62070	023:02:07	194.431	1

(	CIRDCE
ergy	Total A
<b>ergy</b> 165.928	Total A
<b>ergy</b> 165.928 226.115	Total A
ergy 165.928 226.115 180.739	Total A
ergy 165.928 226.115 180.739 178.045	Total A
ergy 165.928 226.115 180.739 178.045 180.240	Total A
ergy 165.928 226.115 180.739 178.045 180.240 637.622	Total A
ergy 165.928 226.115 180.739 178.045 180.240 637.622 237.459	Total A





Abstract Introduction Methods Results 1 Results 2 Conclusion

- SAS Enterprise Miner models outperformed Scikit-learn •
- Gradient boosted models performed best in both programs  ${\color{black}\bullet}$
- occurrences
- Reduced number of missed freezes due to human error

## PREDICT FREEZES IN NATURAL GAS PIPLELINES

Bingi Arnold Kanagwa M.S, Ho Chang Chae, PHD

University of Central Oklahoma

#### Conclusion

Successful implementation of best model significantly reduced the amount of time taken to classify freeze







# SAS® GLOBAL **FORUM** 2020

## USERS PROGRAM

SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. <sup>®</sup> indicates USA registration. Other brand and product names are trademarks of their respective companies.

