Rail Service Failure Prediction: An Integrated Approach Using Fatigue Modeling and Data Analytics

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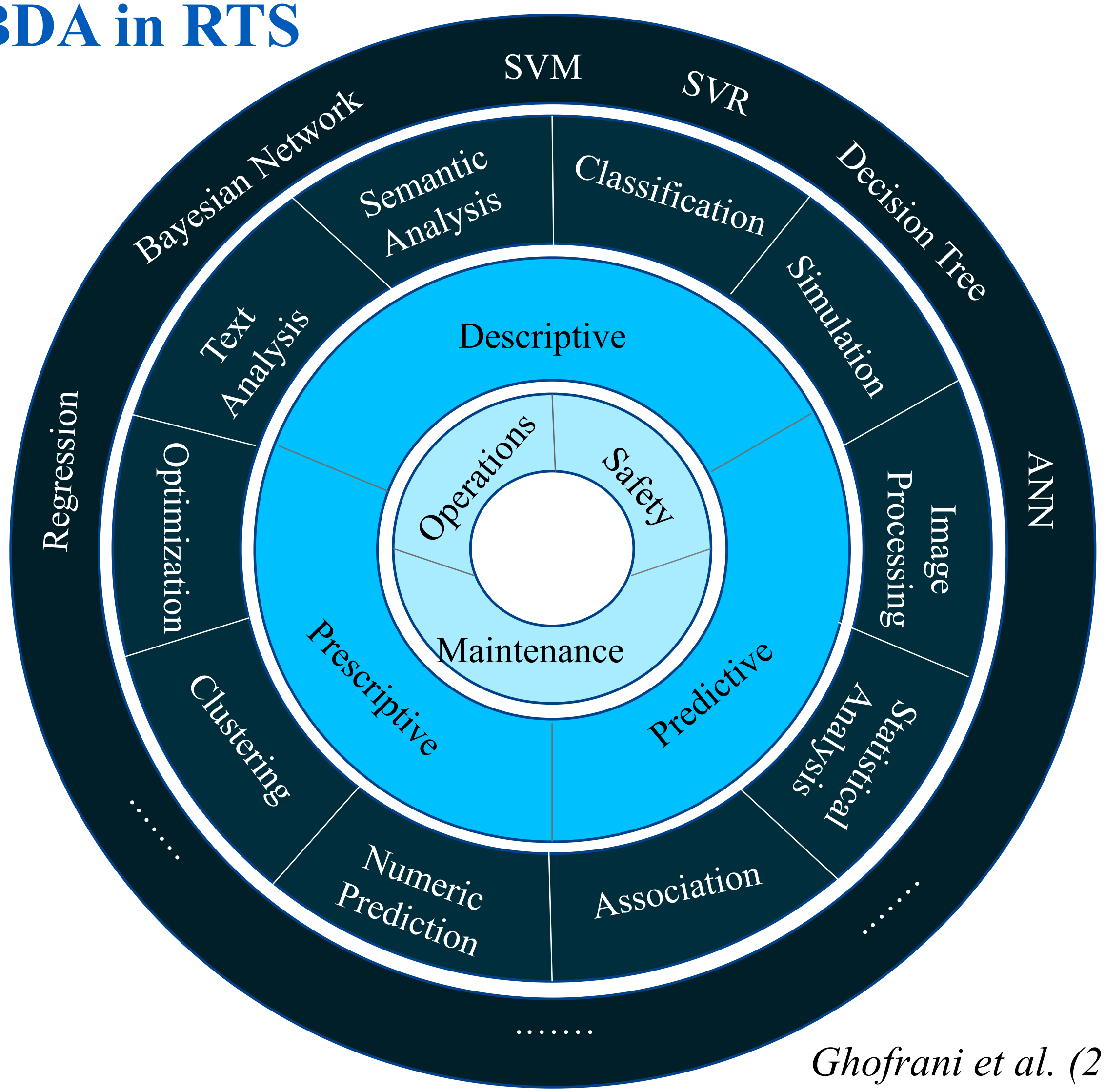
Introduction: BDA in RTS

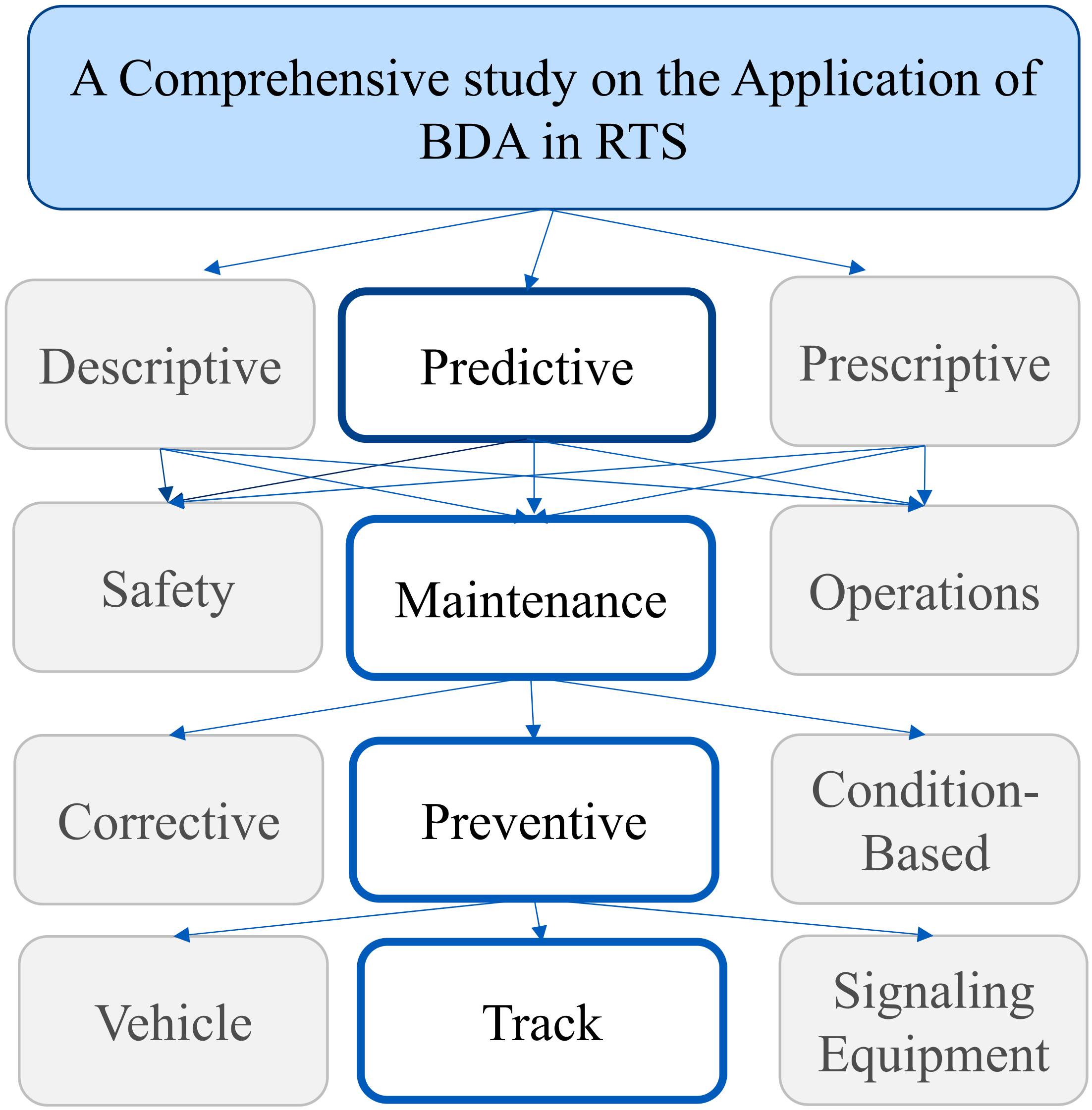


Ghofrani et al. (2018)

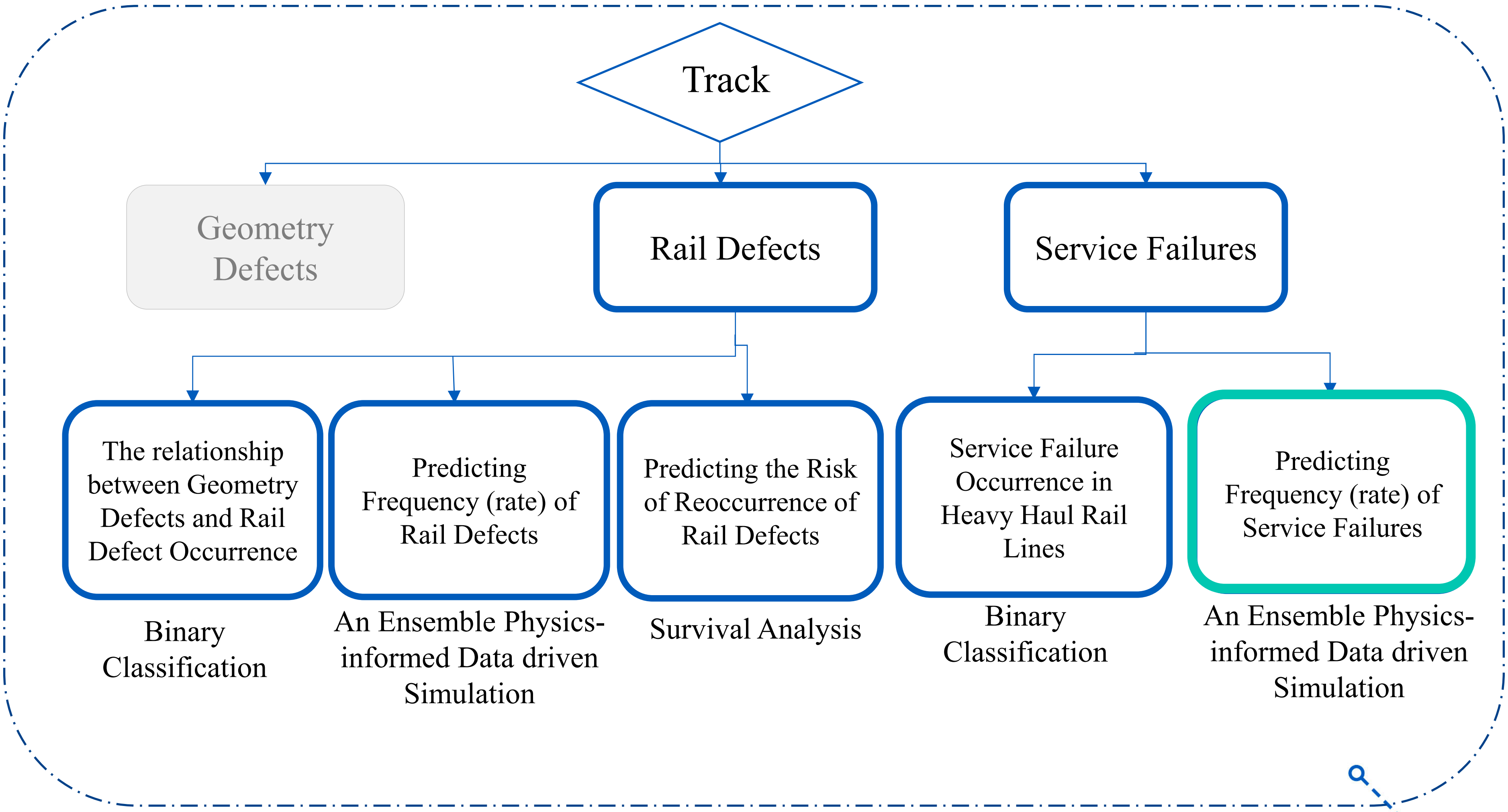
The application of big data analytics in railway transportation systems

University at Buffalo The State University of New York

Research Overview



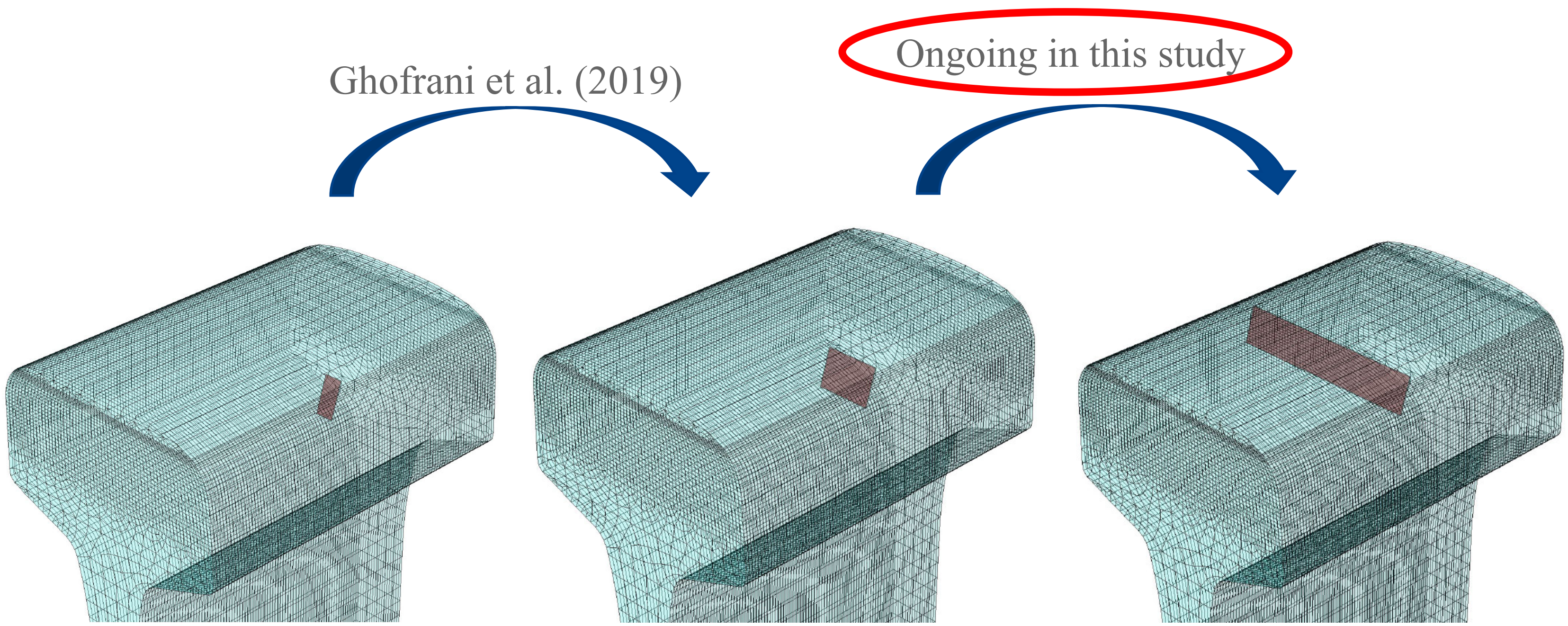
Research Overview-Continued

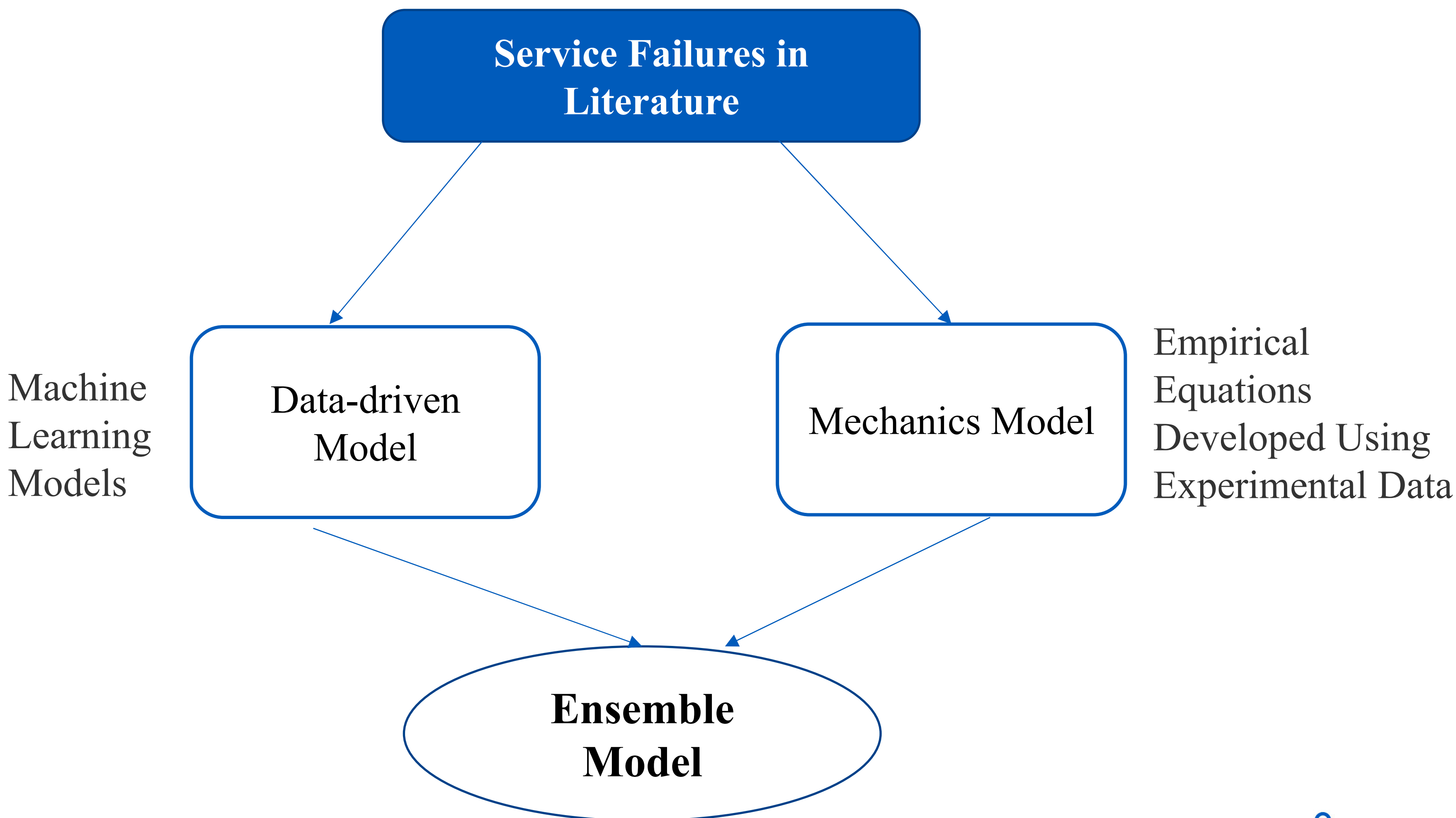


Rail Service Failure Prediction: An Integrated Approach Using Fatigue Modeling and Data Analytics

Research Objective

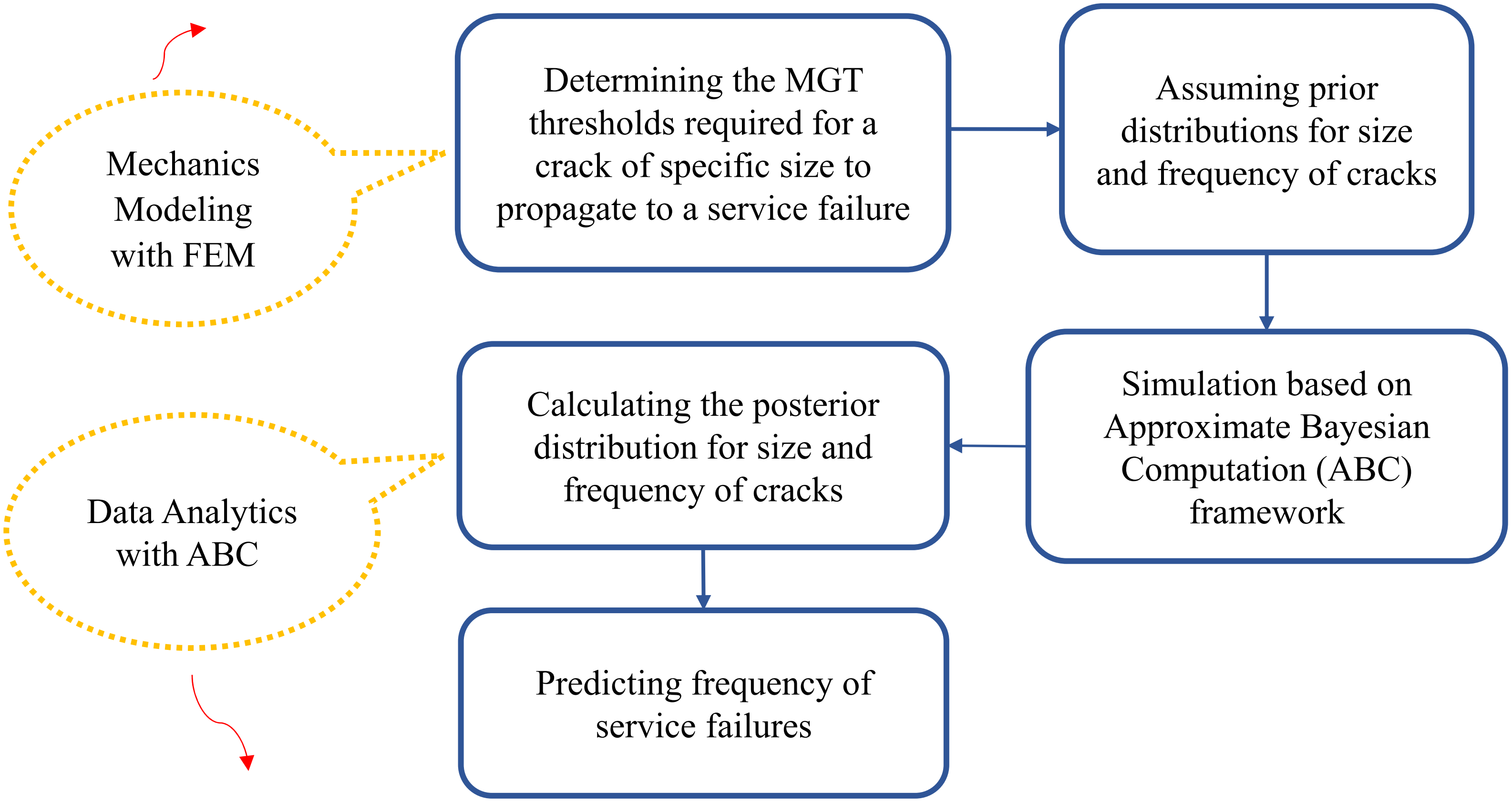
- Develop a data-driven growth prediction model to forecast how an existing defect grows to a complete failure in future?
- Assess the potential (rate) of service failures
- Approach: Fatigue Modeling, combined with Data Analysis




Service Failures in Literature
Machine Learning Models
Data-driven Model
Mechanics Model
Empirical Equations Developed Using Experimental Data
Ensemble Model

Methodology Framework

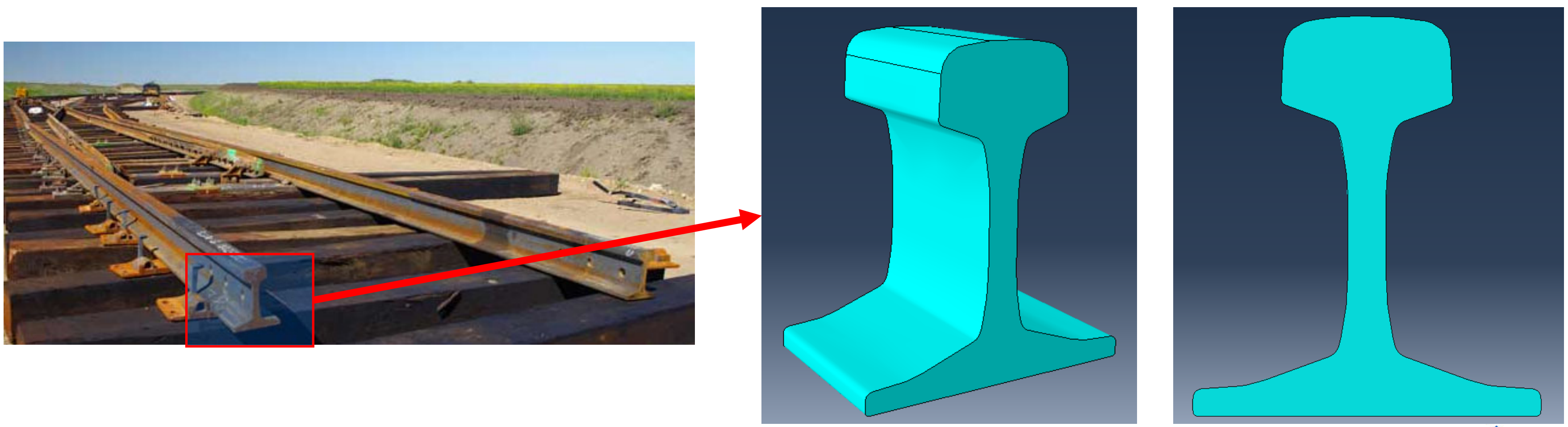
Carried out mainly by structural engineering group



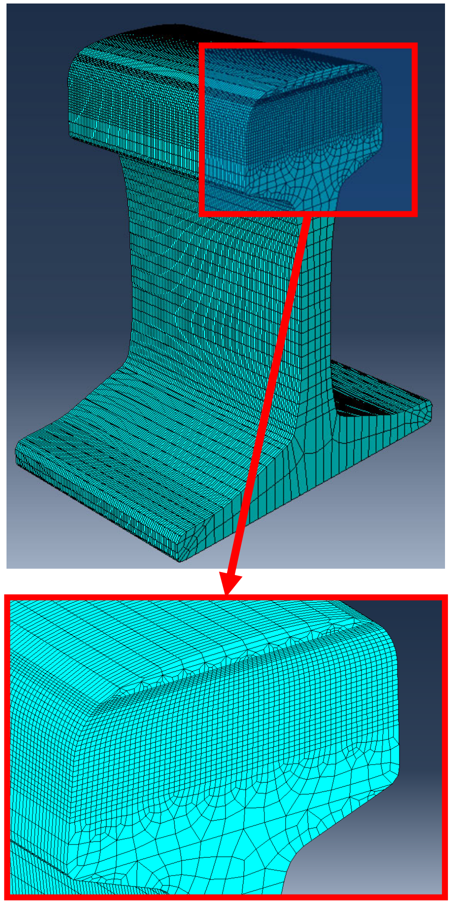
Carried out mainly by transportation engineering group at UB

Methodology: Finite Element Modeling of the Rail

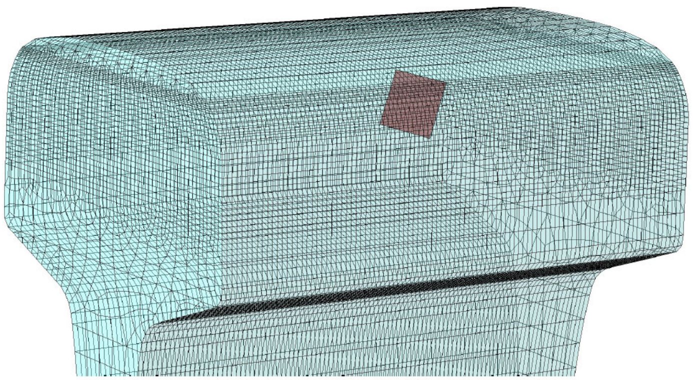
- ❑ Detail fracture (TDD) is mainly concentrated inside the rail
- ❑ A rail element was created in ABAQUS
- ❑ UIC60 (60E1) rail profile geometry was used
- ❑ Elastic steel material was used (E=200 Gpa)



Methodology: Finite Element Modeling of the Rail

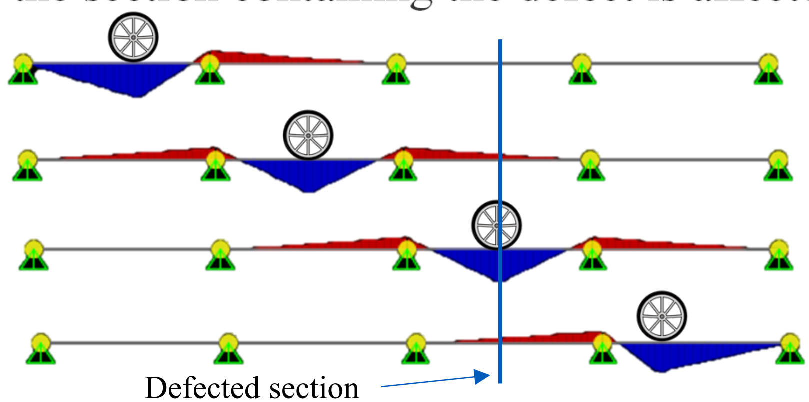


- ❑ Hexahedra structured mesh was used for the rail
- ❑ A defect was modeled inside the rail head
  - ❑ width varied from 15 mm to 55 mm with increments of 10 mm
  - ❑ depth kept equal to 10 mm
  - ❑ inclined with respect to the longitudinal direction of the rail (12.5 degrees) (Zhou et al. 2017)
- ❑ XFEM-crack method was used to overlay defects to the original mesh

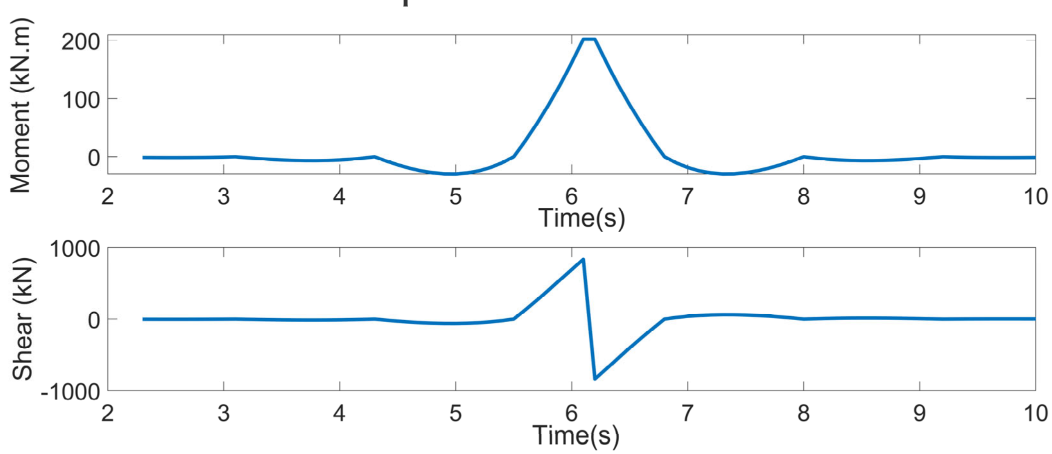


Methodology: Finite Element Modeling the Rail

- Stress induced to the section containing the defect is affected by the location of the wheel

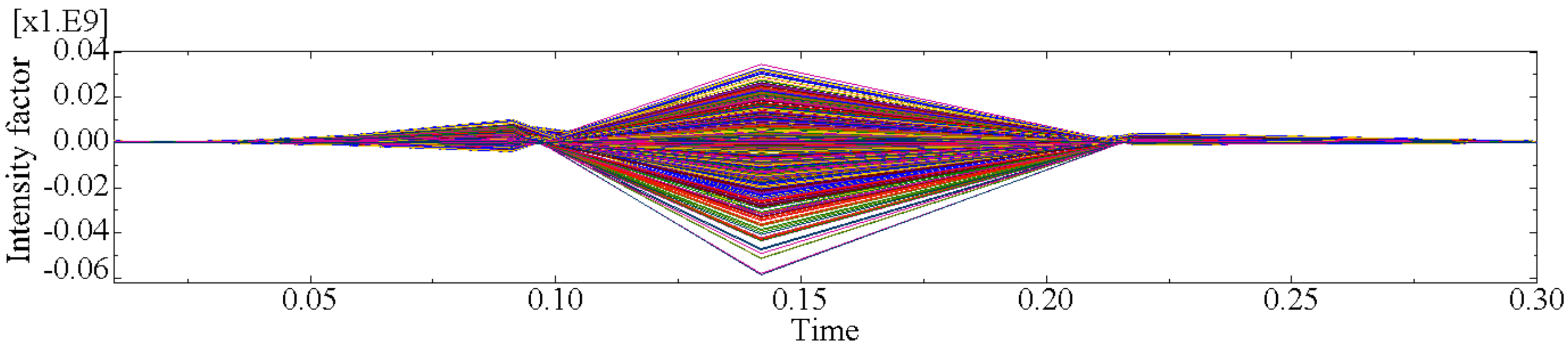


- Moment and shear demand profiles were obtained for the considered section:



Methodology: Finite Element Modeling the Track

- The moment- and shear-demand profiles were introduced, simultaneously, to the rail section modeled in ABAQUS
- Stress-intensity-factor profiles were obtained for each assumed crack width



- Maximum range of intensity factors ΔS_{eff} were extracted and used in the Paris law formula to obtain the cycles required for each crack to propagate to a service failure.

$$N = \frac{\left(a_c^{\,1-m/2} - a_0^{\,1-m/2}\right)}{C \cdot (1 - m/2)} \cdot \left(\Delta S_{eff}\right)^{-m}$$

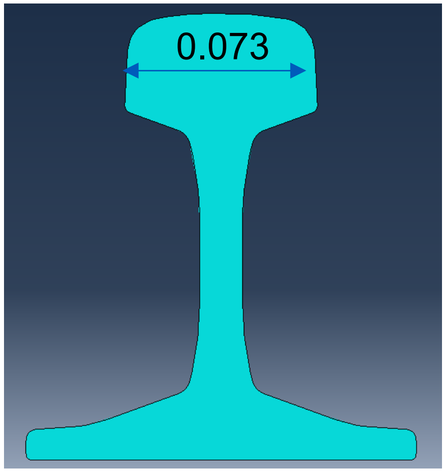
$C = 2.0 \times 10^{-9}$
$m = 3.33$

Where a_0 and a_c are the initial and final defect sizes

Methodology: Finite Element Modeling the Track

- Number of cycles for crack growth is converted to equivalent accumulated traffic load (MGT), by multiplying it by the load from each wheel (Frýba, 1996)

Intensity factor ($MPa \times m^{0.5}$)	Initial crack size (m)	Final size (m)	N	MGT
34.5	0.015	0.073	60098	10.22
35.5	0.025	0.073	30465	5.18
43.3	0.035	0.073	9522	1.62
45.2	0.045	0.073	4945	0.84
44.0	0.055	0.073	2936	0.5



Methodology: ABC Rejection Algorithm

Bayes' Theorem in General

$$\underbrace{p(\theta|D)}_{\text{Posterior}} = \frac{\overbrace{p(D|\theta)}^{\text{Likelihood}}\overbrace{p(\theta)}^{\text{Prior}}}{\underbrace{p(D)}_{\text{Evidence}}}$$

ABC Rejection algorithm

- Start with a sample of parameter points from prior distribution $p(\theta)$.
- Each sample parameter point θ is simulated using an evolution model and simulated data $\check{D}$ is generated.
- If the generated dataset $\check{D}$ varies significantly from the observed dataset D, then the parameter point θ is rejected.

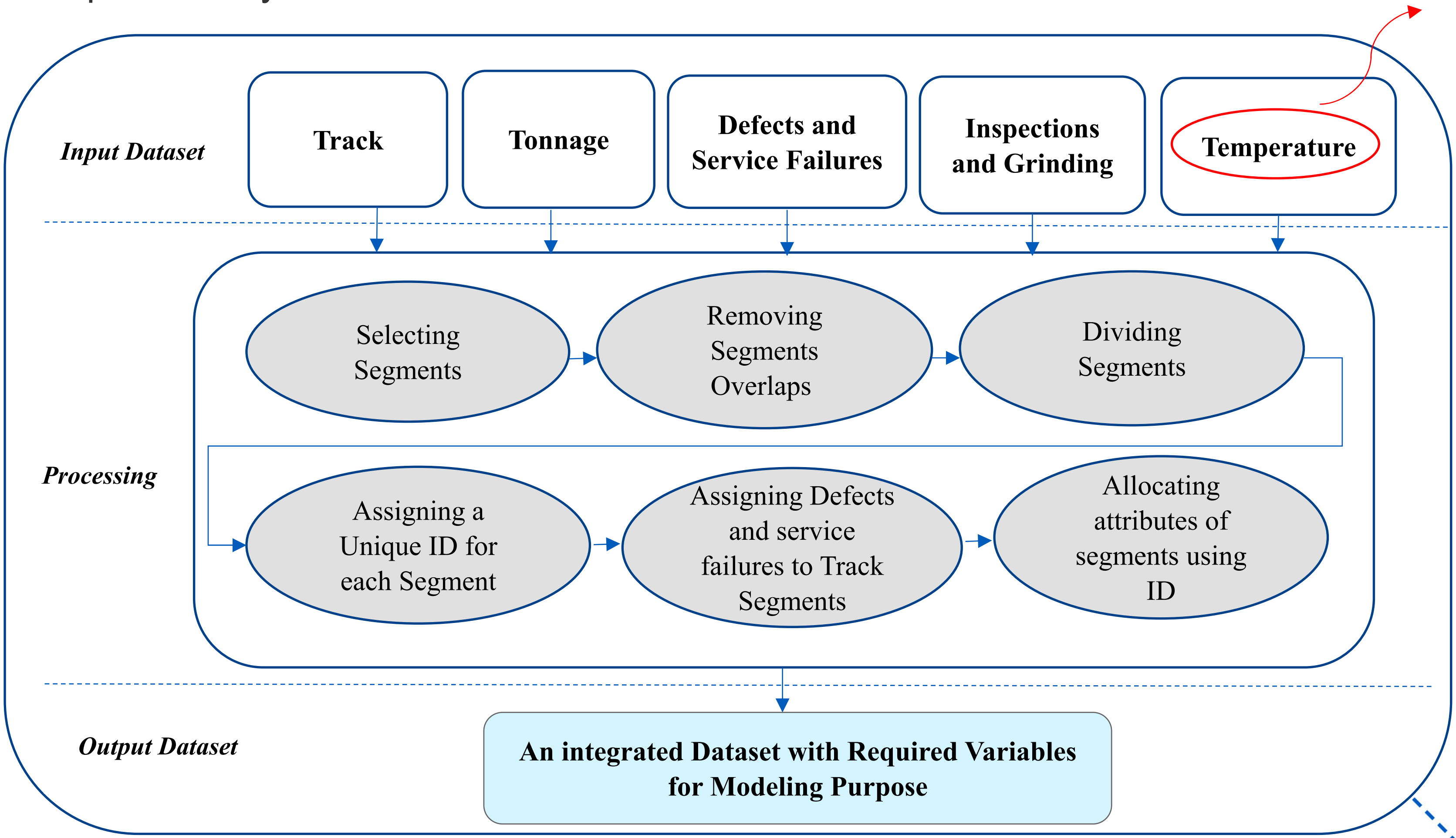
$$p(D, \check{D}) \leq \varepsilon$$

- The outcome of this process is a posterior distribution of parameter points without having to calculate the likelihood

Case Study: Data Preparation

Data provided by FRA from a Class I US Railroad from 2011 to 2016

National Oceanic and Atmospheric Administration (NOAA)



Case Study: Data Description

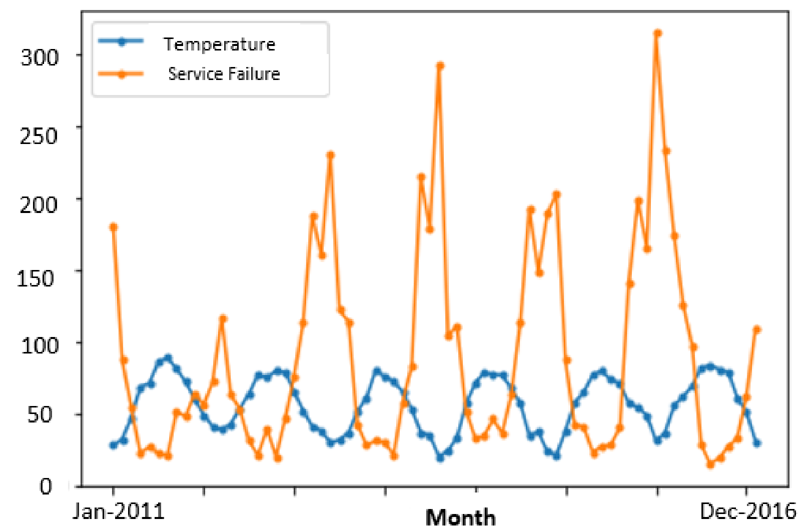
Data has been provided by CSX for six years 2011-2016

Service failure dispersion over the studied US Class I network

Most frequent defect types that are causing service failures

Defect Type	Percentage of total
Ordinary Break	28.38
Transverse Detail Fracture	20.36
Thermite Weld	14.11
Bolt Hole Break	4.90
Crushed Head	4.26

Number of Service Failures vs Average Temperature

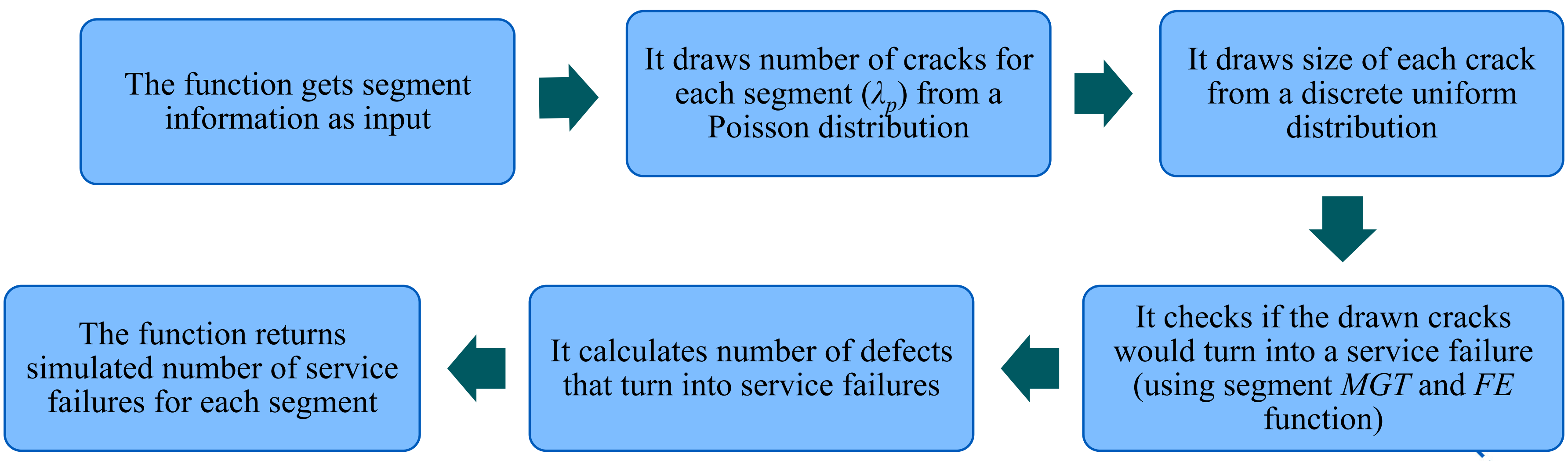


Case Study: Integration of Mechanistic And Statistical Model

❑ Functions

Function *FE*- Input**:** Crack/Defect Size, Output: Required MGT to Complete Breakage (FEM Output)

Function *G*- Input: Segment Information, Output: Simulated Number of Service Failures

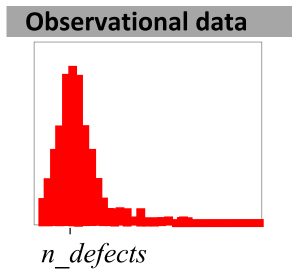


Case Study: Integration of Mechanistic And Statistical Model

❑ Functions- Continued

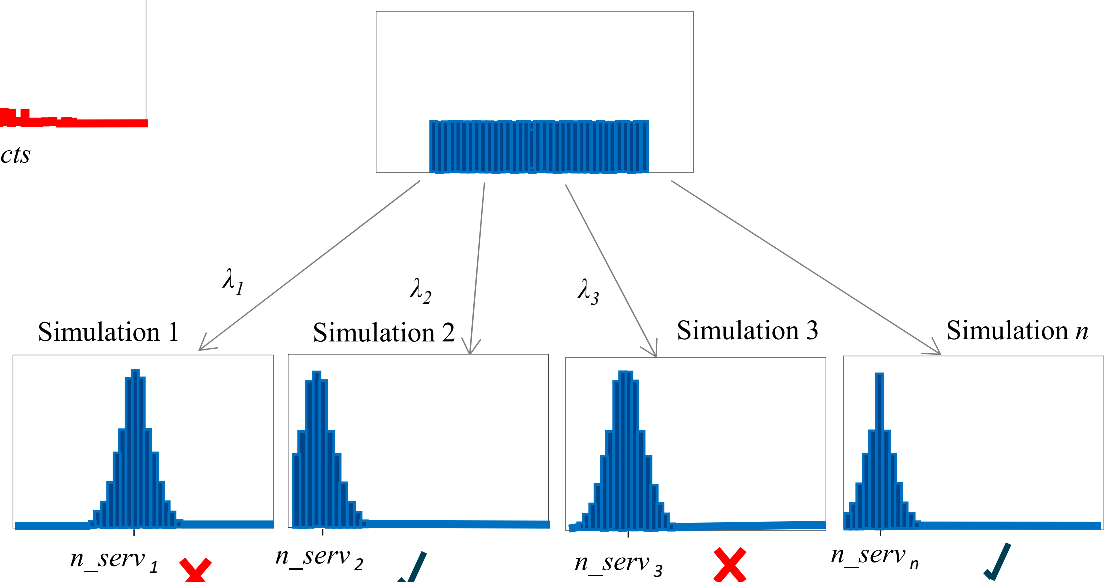
Function *Posterior*- ABC Rejection Algorithm

1. Summary statistic (n_serv) from observational data computed



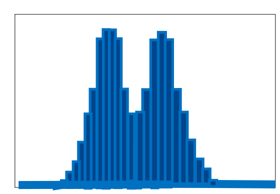
Prior distribution of the model parameter, number of crack (λ): assumed as discrete uniform distribution

2. n simulations are performed by drawing parameter values from the prior distribution for each segment



3. The summary statistic ($\hat{n}\_Serv$) is computed for each simulation using Function G

4. Based on the distance and a tolerance, we decide for a simulation whether its summary statistics to be kept or to be rejected ($Distance(n\_serv_i, \hat{n}\_Serv_i \leq \varepsilon)$)



Posterior distribution of model parameter λ

5. The posterior distribution of λ is approximated using the distribution of parameter values λ_i of accepted simulations

Case Study: Integration of Mechanistic And Statistical Model

❑ Main Algorithm

MGT, Weight, Age, Geometry and Rail Defects,
Inspection, Grinding, Temperature, Curvature, Grade

Partition the dataset into train and test sets

→ For the segments in train set, the posterior distribution of λ is calculated (using *POSTERIOR* Function)

→ Fitting a log-linear regression model on ***train*** data segments, the coefficients of each variable is determined

↓ The computed variable coefficients are used to predict λ for ***test*** dataset

← Simulated number of failures are computed using Function *G*

← The average difference between simulated service failures and observed failures of all segments are calculated as the error metric

Results and Discussions

Item	Proposed Model	Negative Binomial Model
Average predicted No. of defects (annual per mile)	0.257	0.267
Average real No. of defects (annual per mile)	0.269	0.269
MAE	0.243	0.258
Number of Segments in test dataset (three fold cross-validation)	21,230	

Variable	Estimate	Z_value	Pr (>|z|)
(Intercept)	4.14	21.46	0.000
Annual MGT	0.00	15.34	0.000
Weight	-0.03	-9.17	0.000
Count of Geometry Defects	0.02	9.54	0.000
Frequency of Inspection	0.02	5.99	0.000
Presence of Grinding	-0.05	-19.02	0.000
Age*Curve	3.17	12.92	0.000
Average Temperature	-0.09	-28.06	0.000

Contributions of the Study

- ❑ Designing a comprehensive logical methodology framework for data collection, pre-processing, and modeling based on a collection of datasets from different resources in a Class I railroad

- ❑ We develop a hybrid physics-informed statistical model for calculating the rate of service failures

- ❑ The developed method is applied to the prediction of service failure frequency obtained from the inspections in a Class I Railroad.

- ❑ The results of the proposed method is validated by comparing to the results of other popular count-data models in the literature

Conclusions

- Incorporating the physics-based behavior of the railway track on a segment is accompanied with a better estimation of the probable occurrence of service failures.
- Regarding railroad applications, service failure frequency is part of their scoring system to calculate the rail quality and determine the rail renewal for the next year.
- It can help on identifying the black spots in the rail track network to prioritize their corrections.
- Therefore, the outcome of this paper can be used to guide how to make decisions of capital planning for railroads.

Acknowledgement

The data was provided by CSX. Authors would like to express their sincere thanks for the support from CSX.

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Thank you!

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```
Function G (p)
# given the data related to segment p, simulate the number of service failures
    define cracks as a list of size T
    define n_serv as a list of size T initialized with 0
    For t in 1 to T do
        if t>1
            for crack in cracks[t-1] do
                if t*MGT_p > FE(crack)
                    n_serv[t] = n_serv[t] + 1
                    remove crack from cracks[t-1]
                end
            end
        end
        n_cracks ~ Poisson (λ_p)
        For i in 1 to n_cracks do
            cracks[t][i] ~ DiscreteUniform(15, 75)
            if MGT_p > FE(cracks[t][i]) or cracks[t][i] >= 55
                n_serv[t] = n_serv + 1
            end
        end
    end
end
```

function POSTERIOR (*n_serv*, *MGT*)

λ = []

distances = []

for *m* in 1 to *M* do

$\lambda_m \sim$ *uniform*[0, 10]

$\lambda = \lambda + \lambda_m$

n_defect = *G*(λ_m, MGT)

distance = *DITANCE* (*n_serv*, *n_serv*)

distances = *distances* + *distance*

end

use ABC framework to reject distances higher than a threshold and find λ*posterior*

Return λ*posterior*

end

```
For fold=1 to K do
    train_data, test_data = PARTITION(data, fold, K)
    λ = []
    MGT = []
    W = []
    S = []
    For p in train_data do
        λ_p = POSTERIOR(n_serv_p, MGT_p)
        λ = λ + λ_p

        MGT = MGT + MGT_p
        Weight = Weight + Weight_p
        Speed_p = Speed + Speed_p
        Geo_Def_p = Geo_Def + Geo_Def_p
        Inspection_p = Inspection + Inspection_p
        Grinding_p = Grinding + Grinding_p
        Temperature_p = Temperature + Temperature_p
    end
    # fit log-linear regression on train data
    log(λ ) = β+ α_1*MGT + α_2*Speed +α_3*Weight+ α_4* Geo_Def + α_5* Inspection + α_6* Grinding + α_7* Temperature


    # use the regression coefficients to predict λ for test data
    n_defects = []
    n_dêfects = []
    For p in test_data do
        lambda_p = exp(β+ α_1*MGT + α_2*Speed + α_3*Weight+ α_4* Geo_Def + α_5* Inspection + α_6* Grinding+α_7*
Temperature)
        n_serv(hat)_p = G(λ_p, MGT_p)
        n_serv = n_serv + n_serv_p
        n_serv(hat) = n_serv(hat) + n_serv(hat)_p
        print(metric(n_serv, n_serv (hat)))
    end
End
```