Temporal Disaggregation of Precipitation Data Applicable for Climate-aware Planning in Built Environments



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Presenter: Chithral Kodagoda

Exemplary Energy

www.exemplary.com.au

**Colleagues**: David Ferrari, Masoume Mahmoodi, Nihal Abdul Hameed, Trevor Lee, Graham Anderson

#### Introduction

- Several applications in the design and simulation of built environments require input of historical weather data. The accuracy of these models increase proportionally with the resolution of the input weather data.
- Currently, in Australia the available data of precipitation is either lowresolution, e.g., daily or not long enough to produce reliable results.
- In this project we develop two algorithms to generate hourly precipitation data given the known past daily resolution precipitation data.





#### National Construction Code (NCC)

A new amendment brought out in 2019 details new provisions in the NCC that aims to minimize moisture impacts on building physics such as condensation ingress, mold formation, etc.



# Correlation coeff. between weather elements and precipitation





## Markov Chains using TPM

This model generates a sequence of random variables (or states) where the current value is probabilistically dependent only on the value of the prior variable  $s_1 \dots s_i \dots s_n$ 

Current	Next State						
State	0	0.2	0.4	•••	38.2	38.4	38.6
0	0.917	0.043	0.01		0	0	0
0.2	0.697	0.102	0.062		0	0	0
0.4	0.383	0.181	0.135		0	0	0
•				•			
•							
•				•			
38.2	0	0	0		0	0	0
38.4	0	0	0		0	0	0
38.6	1	0	0		0	0	0



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 $s_1 / p_{11} \cdot \cdot \cdot$ 

TPM =

 $p_{1n}$ 

## Steps of Algorithm

- 1. Data preparation process
- 2. Synthesis process



#### **Data Preparation Process**



### Synthesis Process

- 1. Set the first hour's precipitation value with the value for the last hour of the previous day
- 2. For hours 2 to 24:
  - 1. Calculate the cumulative probability of the previous state.
  - 2. Generate a random number between 0 and 1 (denotes probability)
  - 3. Locate the state at which the cumulative probability approaches this randomly generated number and save it as the next state.
- 3. If the sum of the generated hourly signal for the day equals the known daily value, proceed to the next day.





#### **Case Studies**

Four case studies considering the precipitation value at the previous hour are carried out with the following modifications:

- 1. Only Precipitation (no further categorization)
- 2. Categorizing data based on Relative Humidity (RH)
- 3. Categorizing data based on Dew Point Temperature (DPT)
- 4. Categorizing data based on Total Sky Cover (TSC)



Experiment	Classes	Value Ranges for the Corresponding Weather Element		
Exp. 2	low RH medium RH high RH	[5,36) [36,68) [68,100]		
Exp. 3	low DPT medium DPT high DPT	[-127,9) [9,145) [145,282]		
Exp. 4	clear sky scattered overcast	[0,3.33) [3.33,6.66) [6.66,10]		







Root Means Square Error:

Gives us an idea of how the generated signal deviates from the real signal

#### Total number of rainfall hours:

This tells us the total number of rainfall hours detected per case study as compared to the real signal

Number of rainfall hours correctly detected

This metric tells us the percentage of correctly detected rainfall hours.







#### Drawbacks

- > This model is only dependent on the previous states.
- Does not allow us to exploit the high correlations between onset precipitation events and other weather elements.



# **Closing Remarks**

Further improvements to the algorithms that will be investigated include:

- Use of onset events of precipitation rather than all precipitation events
- Investigate different variations of Markov Chains that utilize high correlations between weather elements and precipitation
- effects of implementing raw data with half hourly resolution
- impact of segregating the training and testing data by seasonality

