'Thermal Predictive Algorithms for Smart Readiness of Districts Heating'

Method Development and Implementation at TU Delft District Heating Grid

MSc. Cristina Jurado López, Energy Specialist
cristina.jurado.lopez@deerns.com

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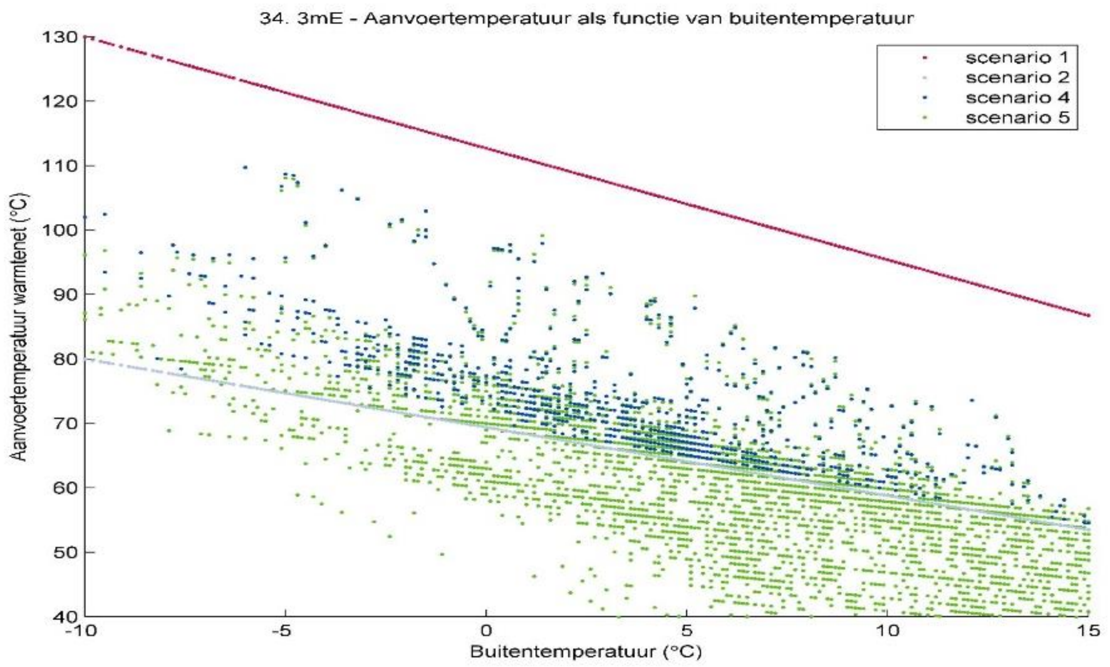
Smart Grid Innovation Programme
('Innovatieprogramma Intelligente Netten' - IPIN)

Transforming the traditional TU Delft heating network towards a **low carbon** heating network

Solution

Dynamic Temperature Supply

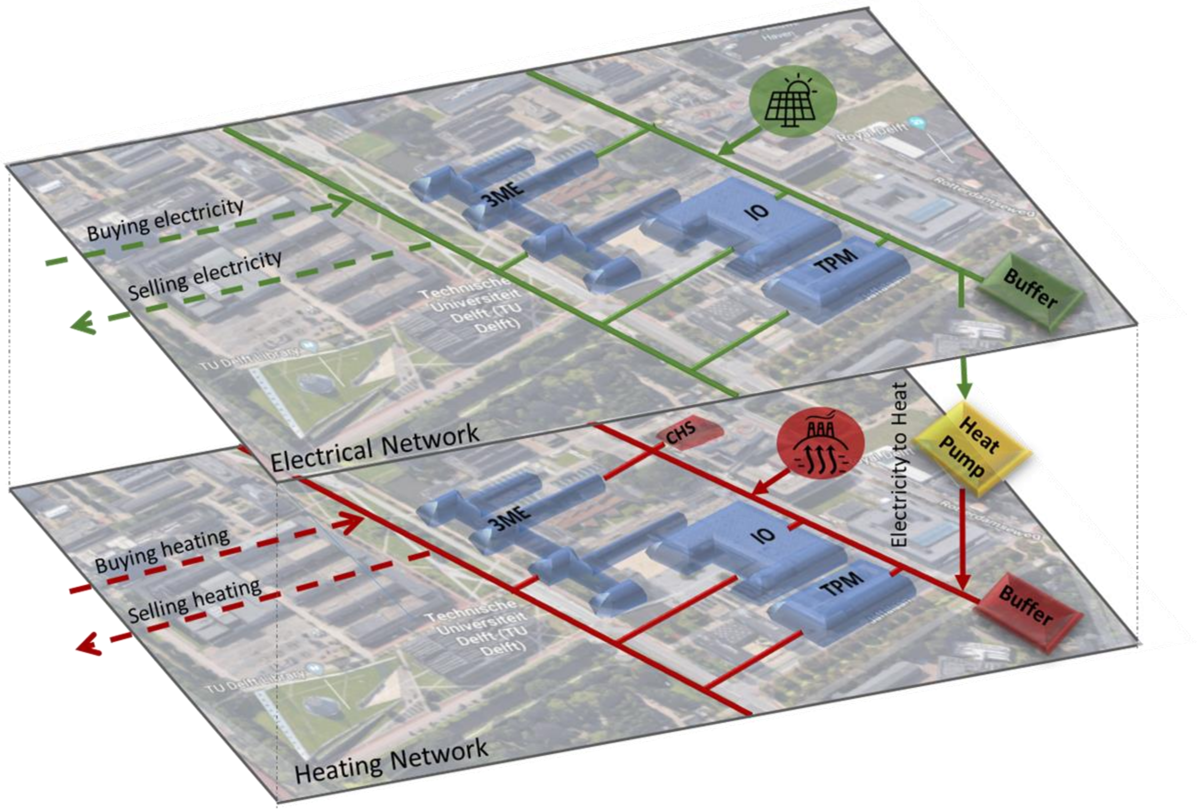
Strategy Change: “*all they want*” →“*all they need*”



Predictive Control

(Traditional BMS towards Smart BMS)

1. Coordinate decentralized heating sources
2. Integrating heating network with other energy flows (electricity, transport, cooling)



How to transform traditional BMS into Smart BMS? Existing Prediction Model Techniques

Law-driven (Physics-based)	Data-driven (Statistics-based)
↑ Physical meaning	↓ Physical meaning
↑ Equations	↓ Equations
↑ Parameters	↓ Parameters
↑ Time&Money	↓ Time&Money
↓ Flexibility	↑ Flexibility

How to transform traditional BMS into Smart BMS?
Existing Prediction Model Techniques

Method 1 Implemented

Law-driven

(Physics-based)

Data-driven

(Statistics-based)

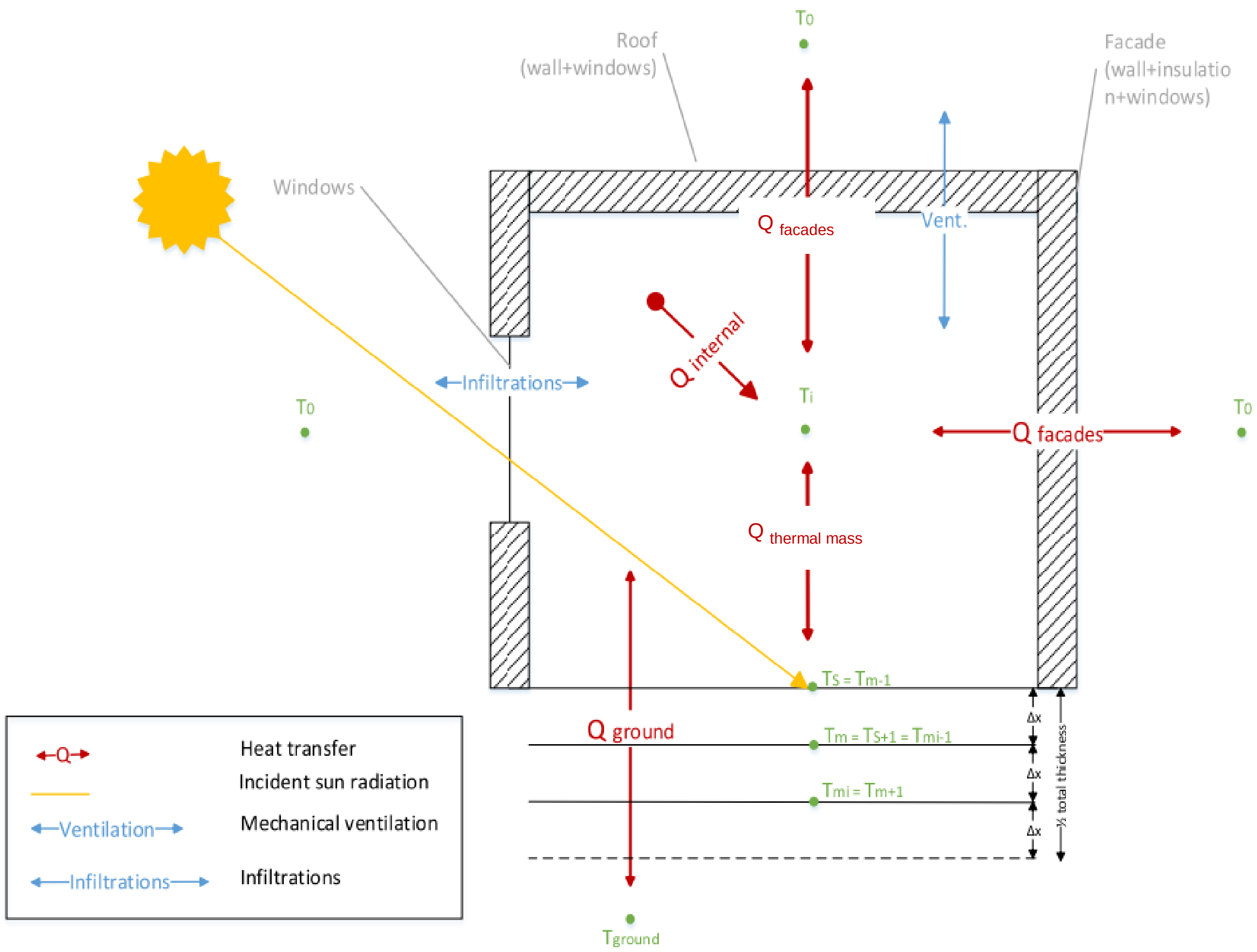
Method 2 Developed & Validated

Data-driven model with physical meaning, fast, simple & flexible?

↑ Physical meaning	↔	↓ Physical meaning
↑ Equations	↔	↓ Equations
↑ Parameters	↔	↓ Parameters
↑ Time&Money	↔	↓ Time&Money
↓ Flexibility	↔	↑ Flexibility

Method 1
Implemented

Physics-based Model (LEA)



Thermal balance during heating mode

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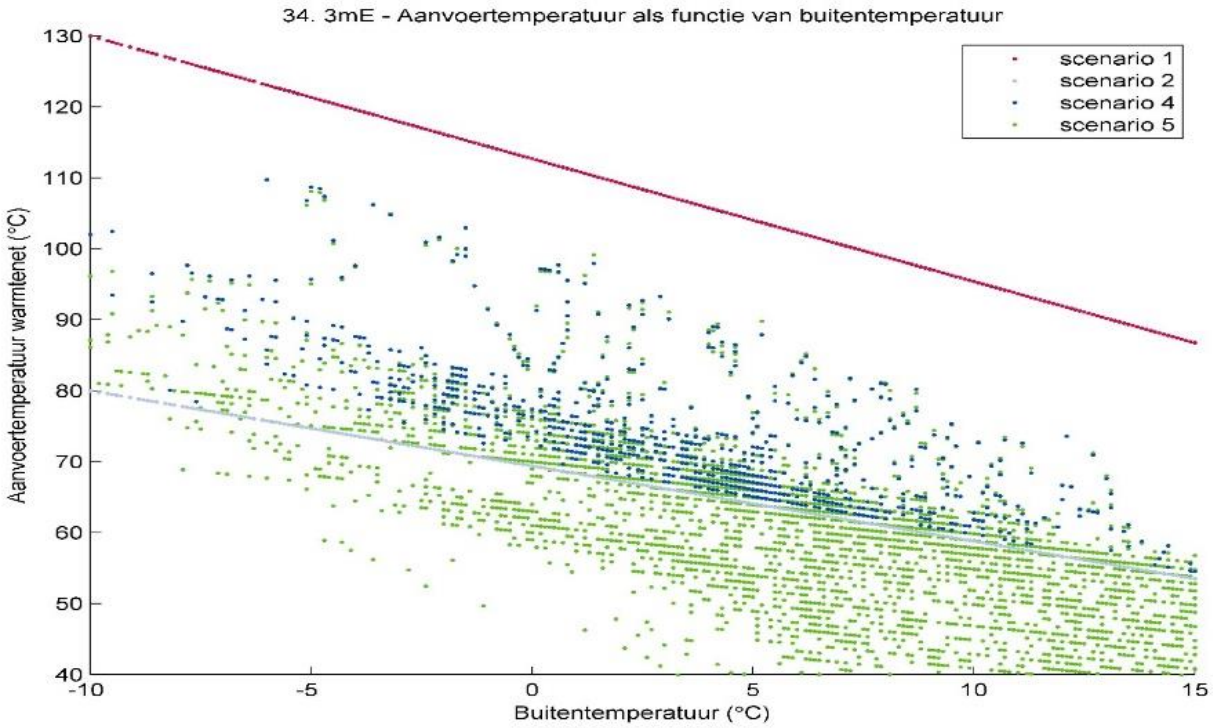
Method 1
Implemented

Results Method 1

Results

- Most of the time **flow temperature (far) below 80 oC**
- Enabling integration **geothermal** energy at TU Delft campus
- Increasing the use of **Combined Heat & Power** due to low return temperature



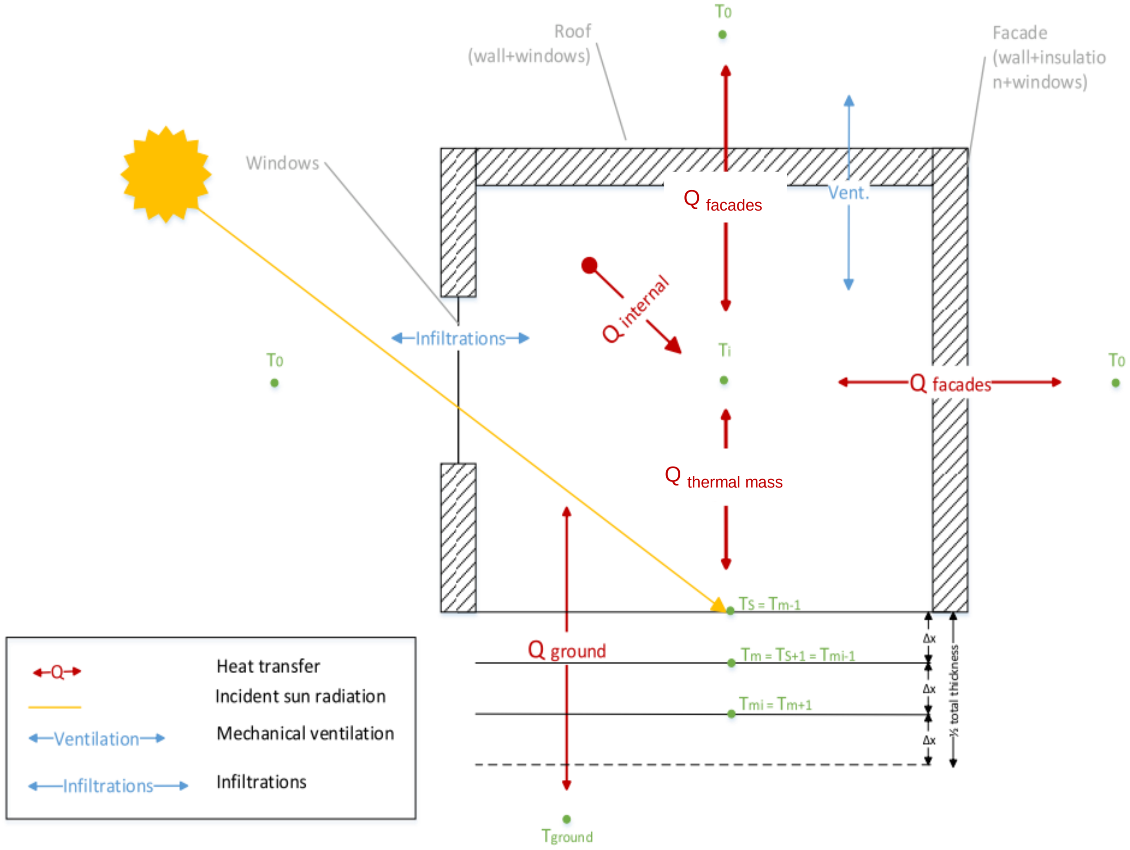
Challenges

- **Complex for large scale** implementation (> 200 parameters to estimate for 20 buildings)
- **Complex programming** (Different language between BMS and coupling of different hardwares)
- **Low flexibility** to introduce changes (building, installations, surroundings) → re-programming required

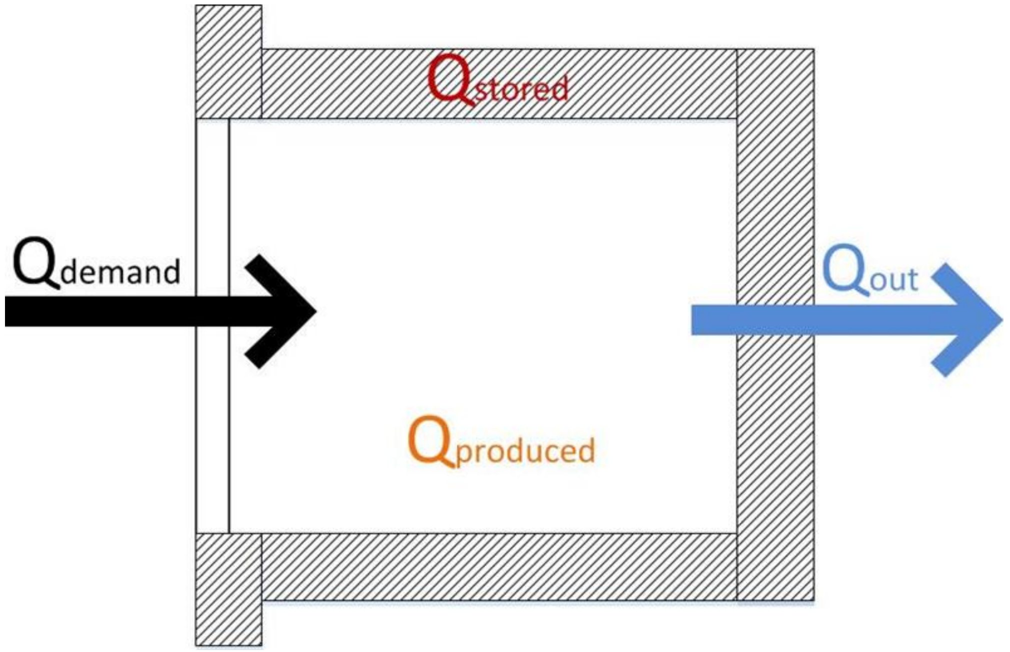
Method 2
Developed & Validated

Data-Driven Model

Thermal model



Simplified thermal model



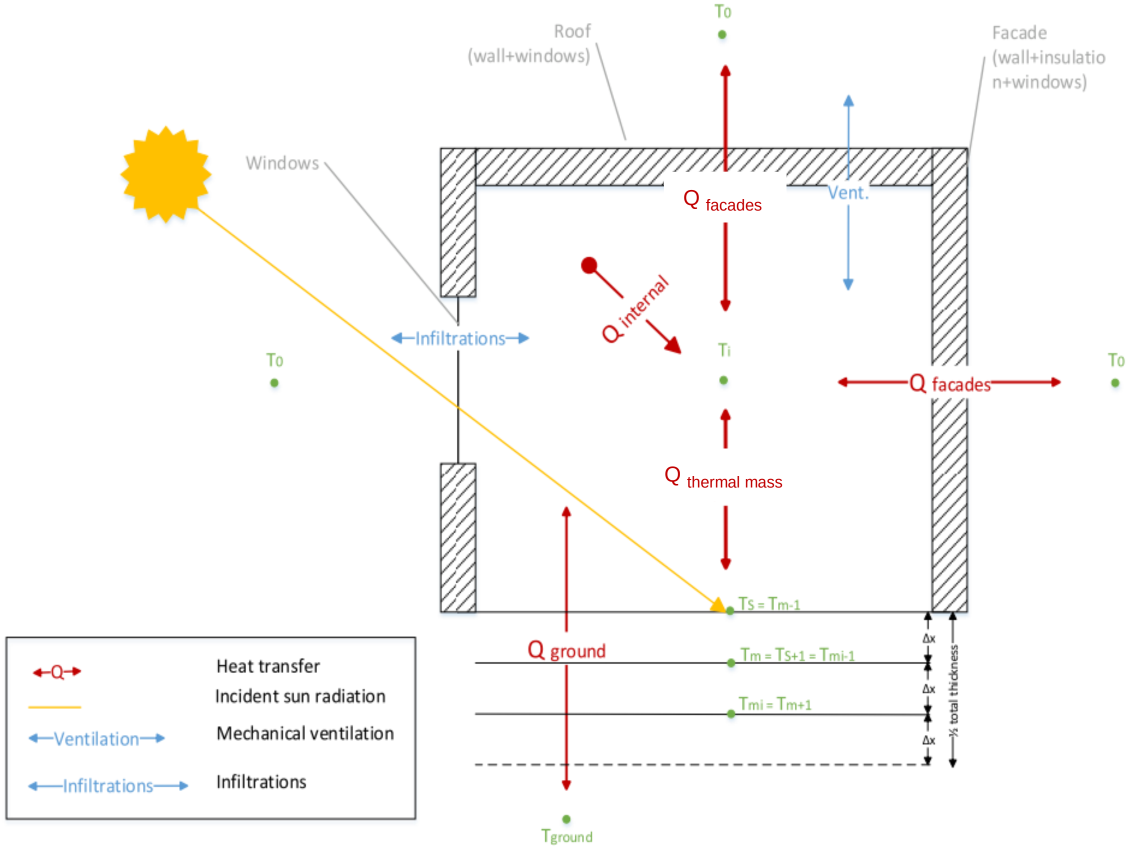
$$Q_{demand} = Q_{out} - Q_{produced} - Q_{stored}$$

$$Q_{demand} = Q_{gr} + Q_{env} + Q_{inf} + Q_{vent} + Q_{sol} + Q_{int} + Q_{th\,mass}$$

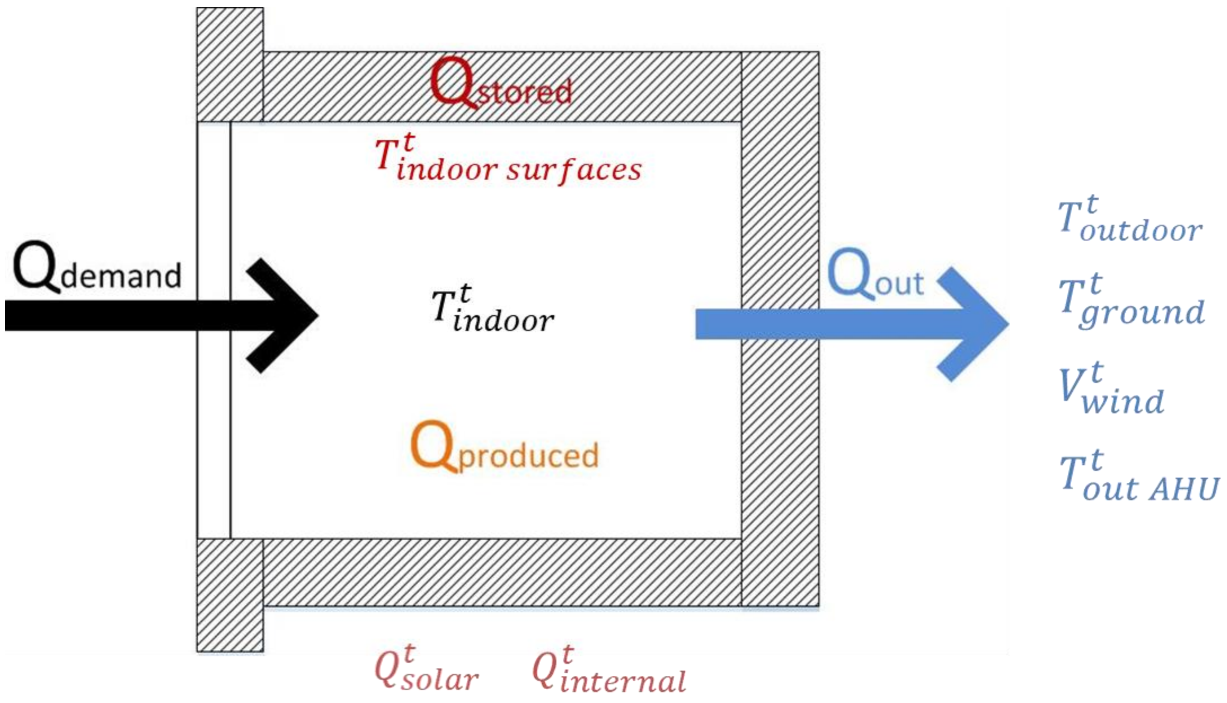
Method 2
Developed & Validated

Data-Driven Model

Thermal model



Simplified thermal model



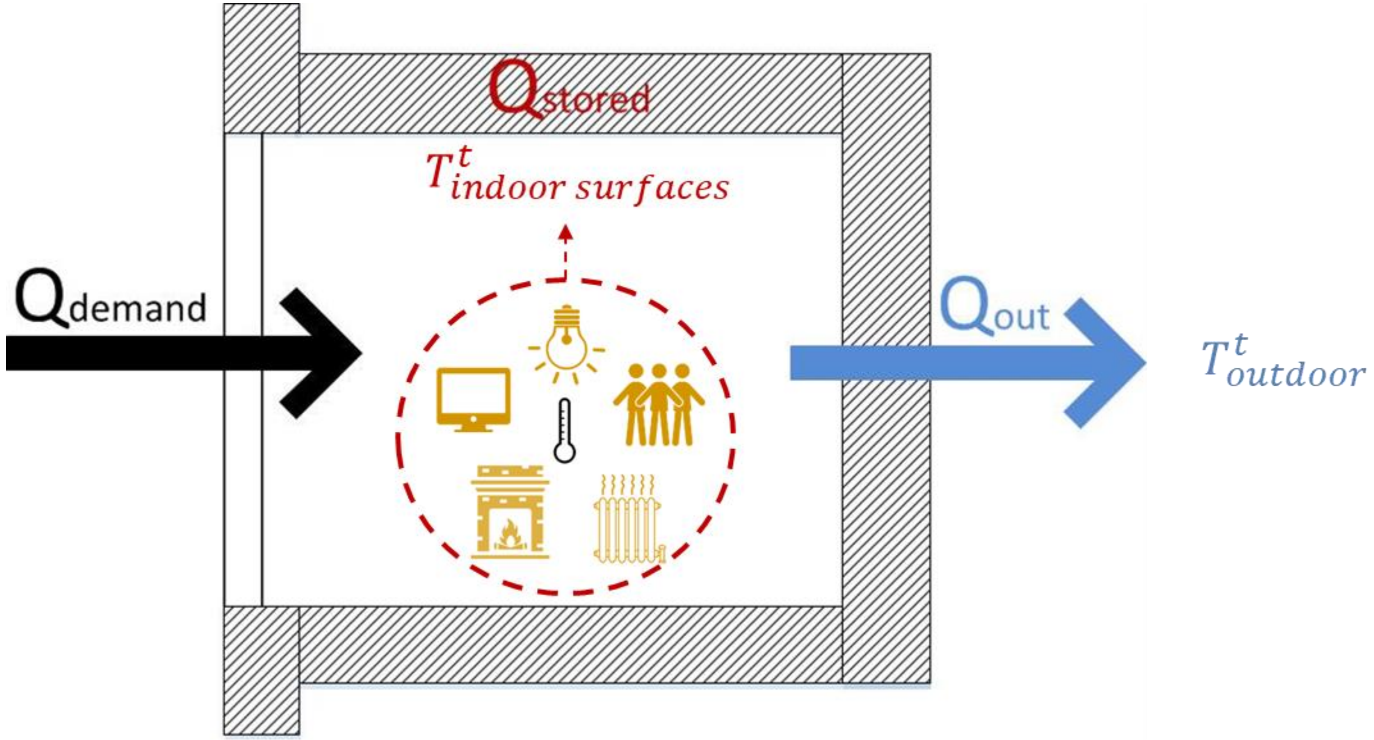
$$Q_{demand} = Q_{out} - Q_{produced} - Q_{stored}$$

$$Q_{demand} = Q_{gr} + Q_{env} + Q_{inf} + Q_{vent} + Q_{sol} + Q_{int} + Q_{th\ mass}$$

$$Q_{demand} = constant + C_1\, T^t_{outdoor} + C_2\, T^t_{indoor} + C_3 V^t_{wind} + C_4\, T^t_{ground} + C_5\, T^t_{out\ AHU} + C_6 Q^t_{solar} + C_7 Q^t_{internal} + C_8 T^t_{indoor\ surfaces}$$

Method 2
Developed & Validated

Data-Driven Model



$$Q_{demand} = constant + C_1(T^t_{outdoor}) + C_8(T^t_{indoor\ surfaces})$$

Able to predict with high accuracy unknown situations

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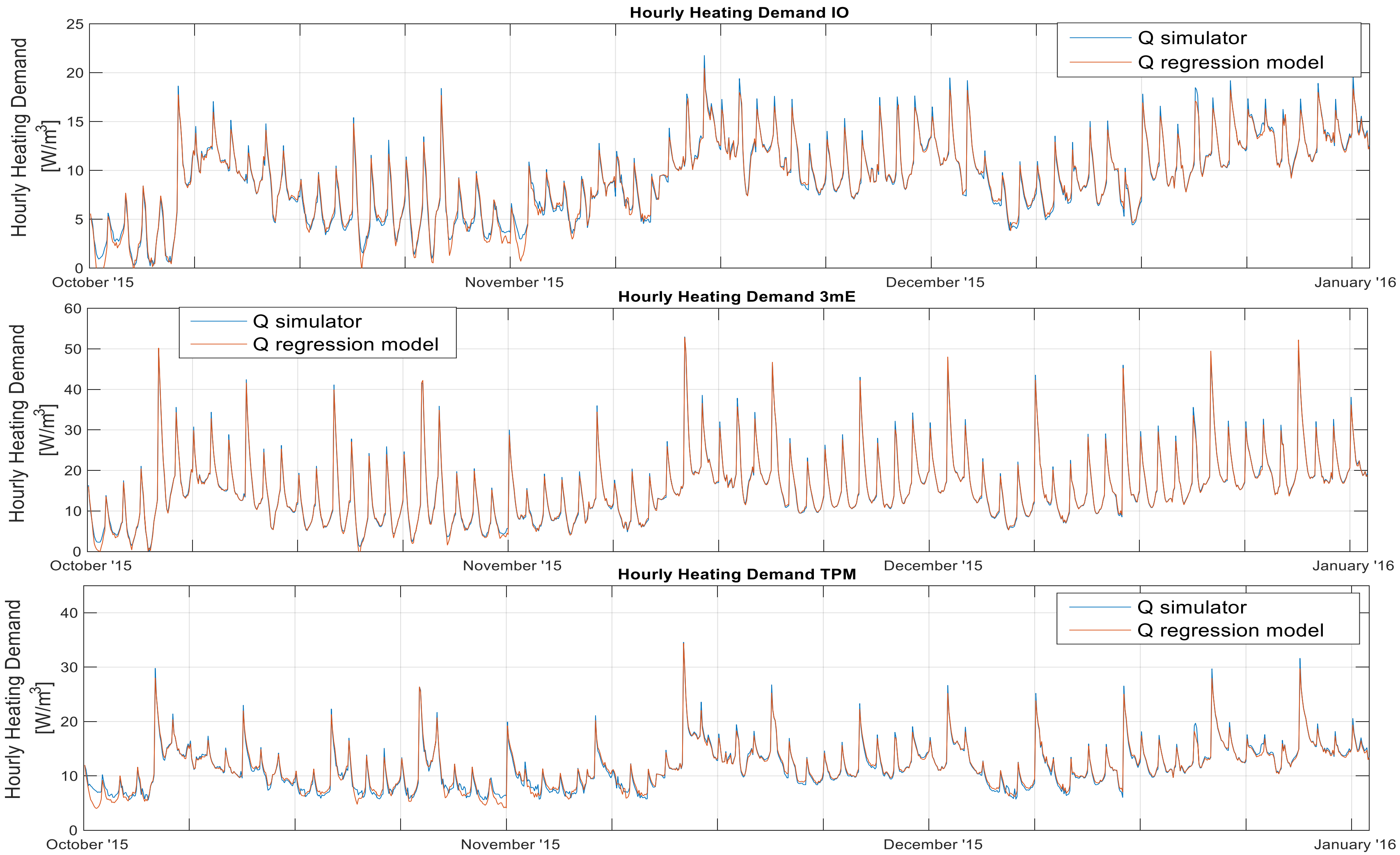
Method 2
Developed & Validated

Results Method 2

$$Q_{demand} = constant + C_1(T^t_{outdoor}) + C_8(T^t_{indoor\ surfaces})$$



Goodness of the fit

Building 1: 97%

Building 2: 99%

Building 3: 96%

Fitting profile of the multivariate regression model for the specific heating demand prediction defined by equation (2) for IO (above), 3mE (middle) and TPM (below), respectively. Data set: weekdays during opening hours from 5th October 2015 until 14th January 2016.

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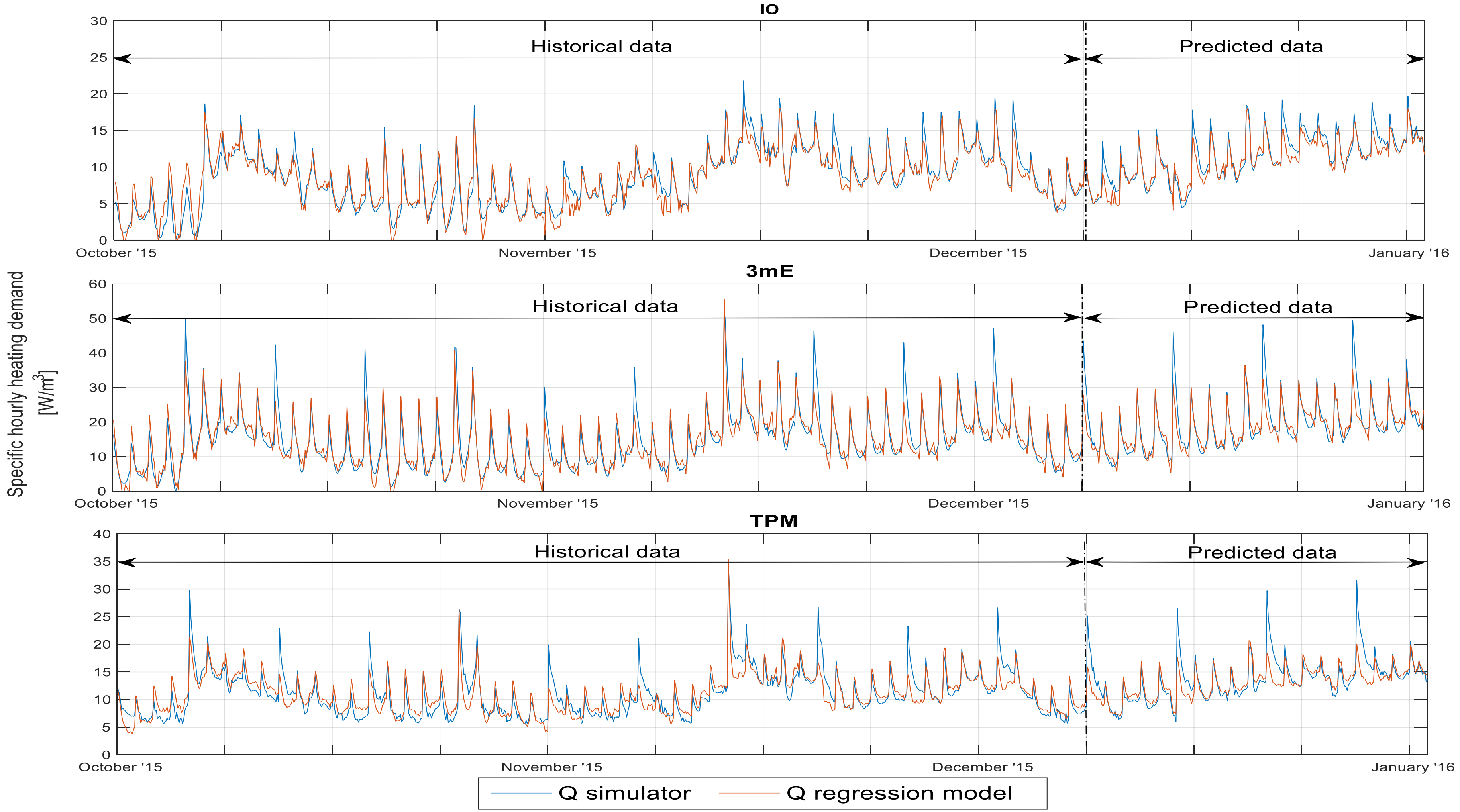
Method 2
Developed & Validated

Results Method 2

$$Q_{demand} = constant + C_1\,T^t_{outdoor} + C_2\,T^t_{indoor} + C_3V^t_{wind} + C_4\,T^t_{out\ AHU} + C_6Q^t_{solar} + C_7Q^t_{internal} + \boxed{C_9Q^{t-1}_{internal} + C_{10}Q^{t-3}_{solar}}$$



Fitting profile of the multivariate regression model 2 based on the data set October-December 2015 for IO, 3mE and TPM, respectively.

Goodness of the fit

Building 1: 90%

Building 2: 83%

Building 3: 73%

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Method 2
Developed & Validated

Results Method 2

$$Q_{demand} = constant + C_1\, T^t_{outdoor} + C_2\, T^t_{indoor} + C_3 V^t_{wind} + C_4\, T^t_{out\ AHU} + C_6 Q^t_{solar} + C_7 Q^t_{internal} + \boxed{C_9 Q^{t-1}_{internal} + C_{10} Q^{t-3}_{solar}}$$

REHVA
Federation of European Heating, Ventilation and Air Conditioning Associations

Fitting profile of the multivariate regression model 2 based on the data set October-December 2015 for IO, 3mE and TPM, respectively.

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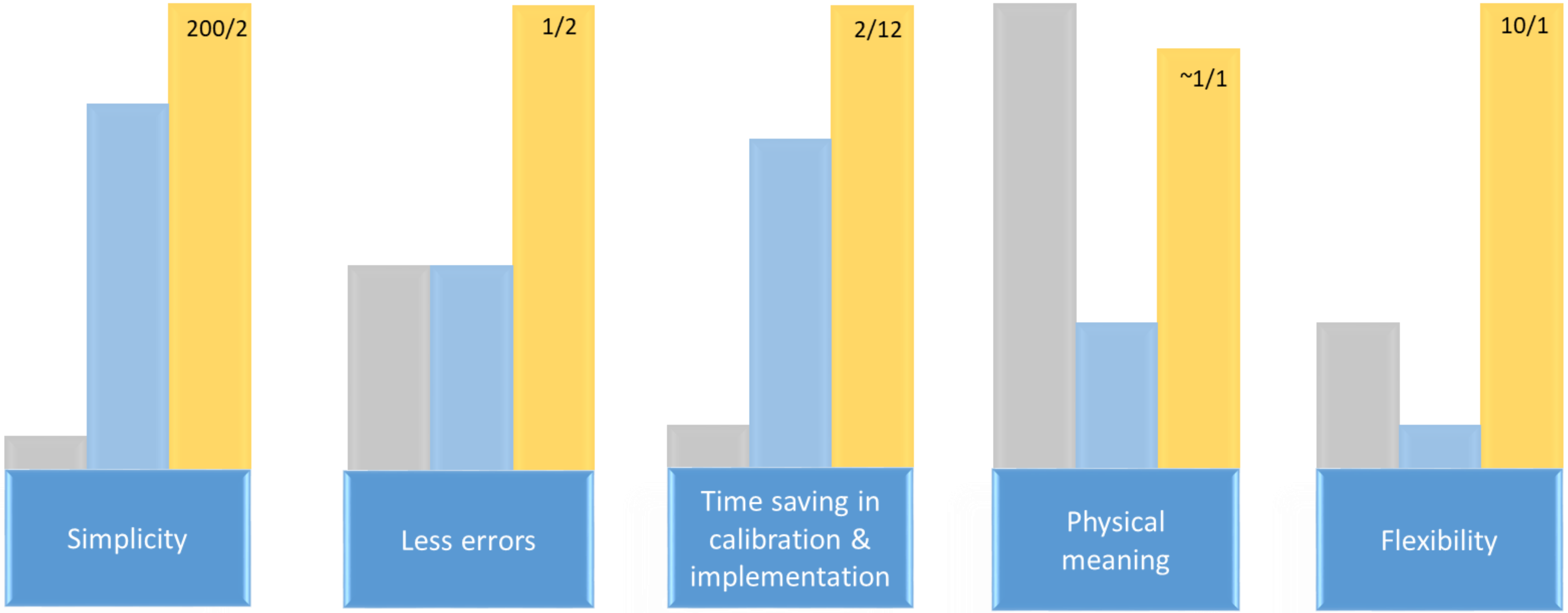
Methods Comparison



	Simplicity	Less errors	Time saving in calibration & implementation	Physical meaning	Flexibility
Law-Driven model	- >200 variables - Complex to detect relations	- Introduction errors (parameters estimation)	- Inventory & calibration - Programming interaction with other softwares	+ Physical meaning	- Complex to introduce new physical relations with 'unknowns'
Data-Driven model	+ <10 variables - Large data set (>1 year)	- Introduction errors (no physical meaning)	+ Can be automatized + introduced in BMS	- No physical meaning	- Difficult to introduce physical meaningful parameters
Developed model	+ 2-6 variables - Small data set (<2 months) + Simple to detect relations	+ No introduction errors (all 'unknowns' accounted)	+ Can be automatized + introduced in BMS	+ Physical meaning	+ Easy to introduce any physical meaningful parameters

https://tvvlconnect.nl/thema/duurzaamheid-circulariteit/documenten/1711-eenvoudige-voorspellende-algoritmes-om-wijken-klaar-te-maken-voor-slimme-verwarming

Would you like more information? Contact me!

Cristina Jurado López
Energy Specialist
Cristina.jurado.lopez@deerns.com
+31 6 50 16 34 27