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ENHANCING HOUSEHOLD-LEVEL OPERATIONAL DECISION MAKING WITH MACHINE LEARNING

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Motivation and Problem

- Agent-based modeling is a comprehensive tool for analyzing the electricity market.
- Considering the behavior of individual household (HH) actors (PV, HP, EV) is important.
  - Traditional aggregation neglects diversity in individual decision-making processes.
  - Influence of varying attributes of individual actors is overlooked.
- Direct modeling of individual HH actors is challenging w.r.t. to resources.

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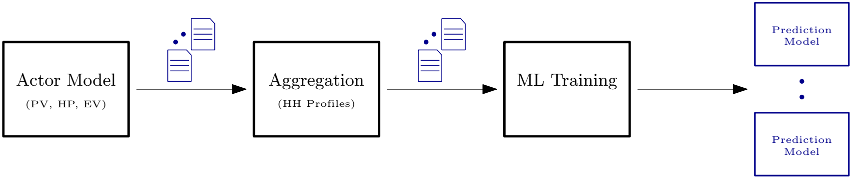
Solution:
An accurate prediction of the aggregated behavior of these actors

The Process



- Actor Model: The actual optimization models for PV, HP, and EV.
- Aggregation over the population represented by each HH profile.
- HH profiles fine-grainity differs among technologies, e.g., Weather-Locations
  - are impotent in PV and HP profiles,
  - can be ignored in EV profiles.
- Result: One prediction model for each technology and HH profile.

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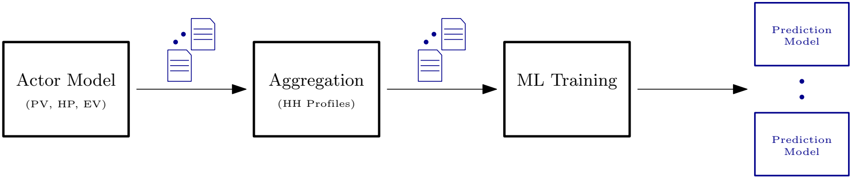

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$\Rightarrow$
Reduces the complexity of ABM models to
one agent per technology and HH profile.

Challenges of Training the Prediction Models

1. Multiple input variables and one target variable.
2. Input variables and their forward and backward windows are fixed by the corresponding actor model.
3. Each input variable has an individual forward and backward window.
4. Input and output are time series (TS).

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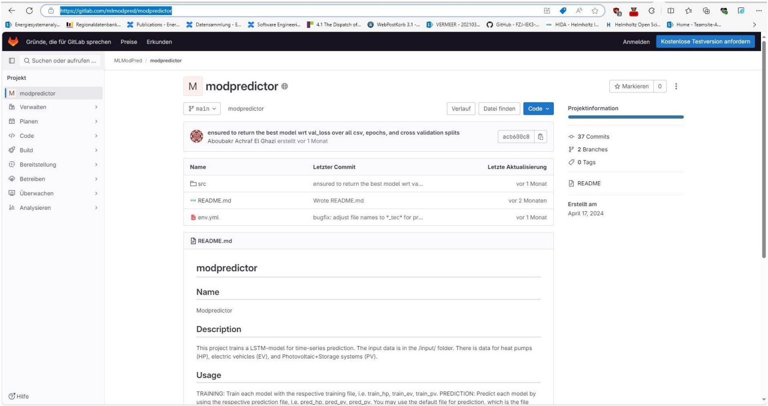
especially 3., makes the use of popular
TS forecasting frame works challenging

Our Solution: ModPredictor

- https://gitlab.com/modpredictor



Our Solution: ModPredictor

- Language: Python.
- ML Dependencies: scikit-learn, keras, tensorflow.
- Uses LSTM with variable sizes and deepness (not yet automatic).
- Two approaches for variable forward and backward windows.
- Ignore concrete time and focus on sequences.

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Will be soon available @GitLab as open source

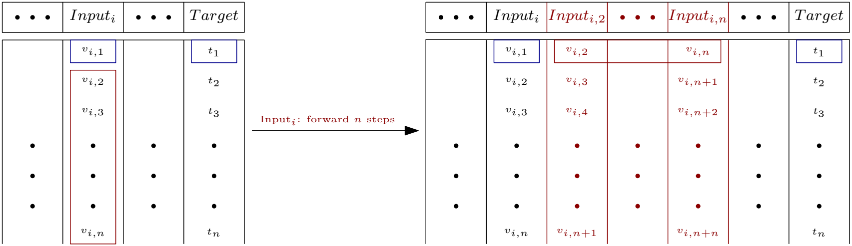
Variable Forward and Backward Windows – *PV Example*

```yaml
file_paths_train:
  - "./load_pv_MH2_Berlin.csv"
test_ratio: 0
time_var: "TimeStep"
input_vars:
  EnergyGenerationPerMW:
    Forward: 1
  StoredMWh:
    Forward: 1
  ProsumersLoadInMW:
    Forward: 1
  SalesPriceInEURperMWH:
    Forward: 24
target_vars:
  GridInteraction:
    Backward: 24
model_dir: "output/pv_model"
scaling:
  - "input"
  - "target"
epochs: 100
```

```yaml
file_paths_train:
  - "./load_hp_BAU_Kiel.csv"
test_ratio: 0
time_var: "TimeStep"
input_vars:
  ambient_temperature:
    Forward: 48
  solar_radiation:
    Forward: 48
  price:
    Forward: 48
  tapping_profile:
    Forward: 48
target_vars:
  aggregated_consumption:
    Backward: 48
model_dir: "output/hp_model"
scaling:
  - "input"
  - "target"
epochs: 100
```

```yaml
file_paths_train:
  - "./load_ev_profile0.csv"
test_ratio: 0
time_var: "timestamp"
input_vars:
  price_EURkWh:
    Forward: 96
  available_charging_kW:
    Forward: 96
  elec_consumption_kWh:
    Forward: 96
  battery_level_kWh:
    Forward: 96
target_vars:
  optimised_load_kW:
    Backward: 24
model_dir: "output/ev_model"
scaling:
  - input
  - target
epochs: 100
```

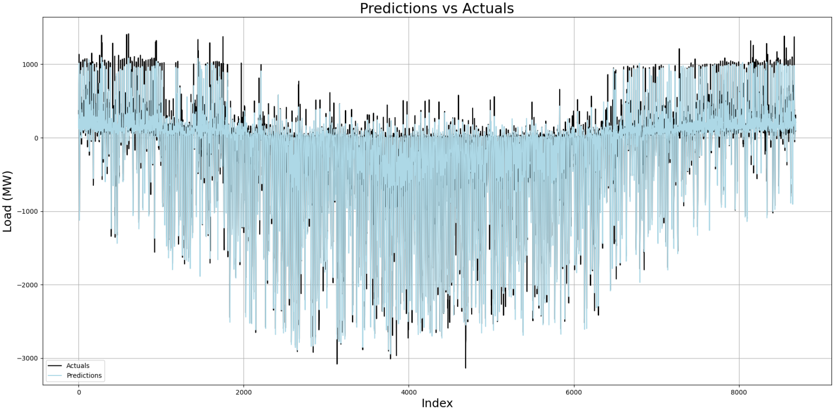
Variable Forward and Backward Windows – *Streamlining*



- General – *usable with any NN*
- Exact – *no information change*
- However, not feasible for big training data and moderate hardware
- Alternative: Padded tensors, Runtime improvement: $>$ 1day $\Rightarrow <$ 1Hour.

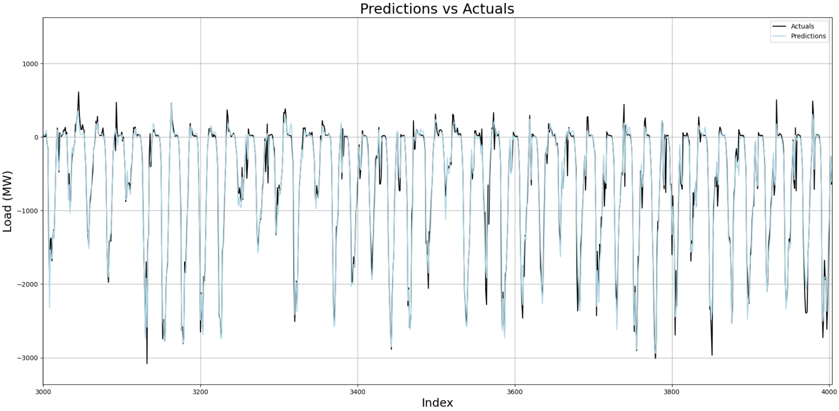
ModPredictor – *PV Results*

ENTIRE TEST SET:



ModPredictor – *PV Results*

ZOOM-IN: entry index 3000 – entry index 4000



ModPredictor – *All Results*

MODEL	TRAINING	VALIDATION	TEST	MAE (MW)
PV	8760	CrossVal 1/4	8760	87.80
HP	8760	CrossVal 1/4	8760	241.99
EV	35040	CrossVal 1/4	35040	423.56

Results and Conclusion

- Acceptable predictions for PS, HP, and EV.
- Enhanced understanding of the impact of individual household decision-making.
- ML techniques provide a scalable solution for modeling diverse actor decisions.

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THANK YOU!

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