Friedrich-Alexander-Universität
Technische Fakultät

Prediction of Household-level Heat-Consumption using PSO enhanced SVR Model

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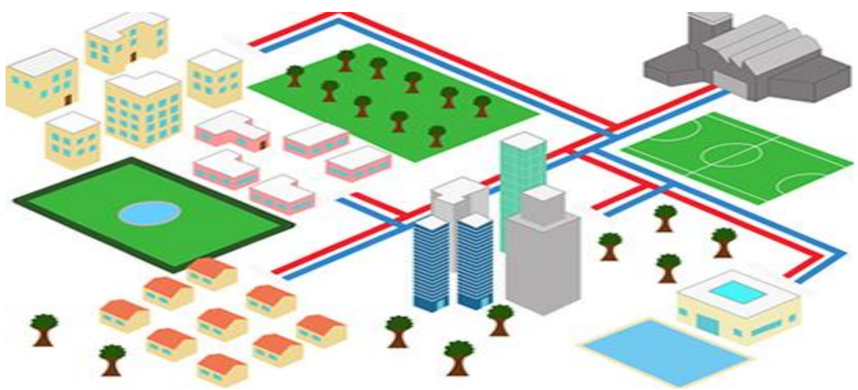
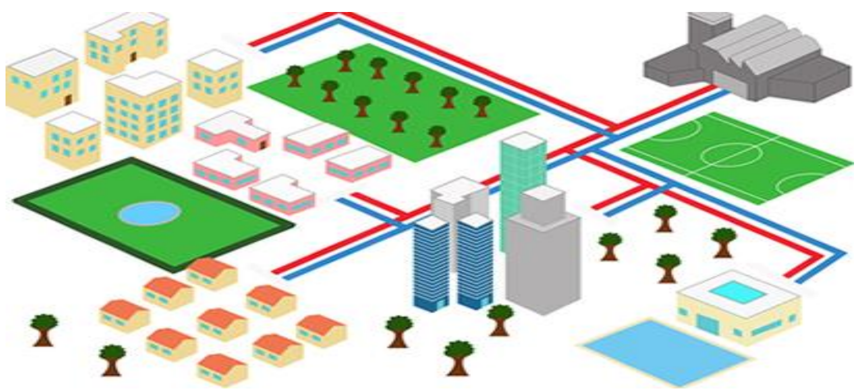
Motivation

- Key-factor behind climate-change is CO2 emission.
    - According to the United Nation Environment Program, urban areas are '**responsible for 75% of global CO2 emissions**'. [1]
- Considerable source of CO2 emission: District Energy System. [2]
- Supply of **demand-driven thermal energy** in DES can reduce CO2 emission.
- Utilities tend to over-supply to ensure the security of the energy supply.
- Consumption data acquired by smart meters in customer's side is used only for billing purposes.
- Therefore it is important for the utility to accurately predict the demand of thermal energy based on the pattern of consumption.



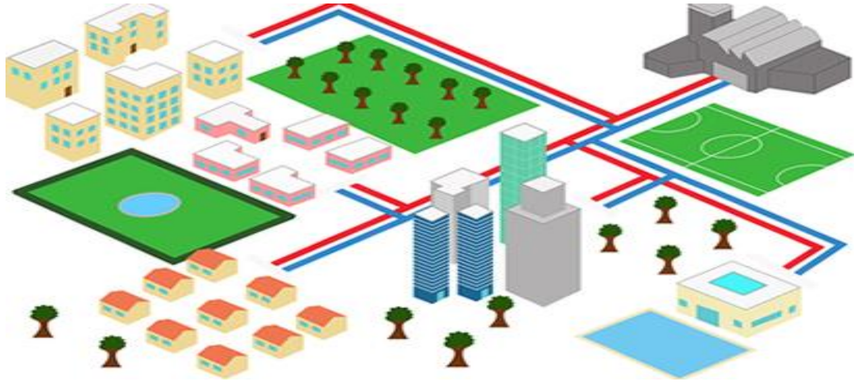
Motivation (contd.)

- **Limited prediction accuracy** of statistical forecasting models, viz. **AR**[3]**, ARIMA**[4,5] **or, SARIMA**[6] due to underlying nonlinearity.
- **ANN**s tend to get trapped in local optima.[7]
- **LSTMs** are capable to model the trend, seasonality, residual and external factors but training of such model **requires large amount of data** (not supported by many utilities).[8]
- **SVR**-based methods perform promisingly [9][10][11]but the **choice of hyper-parameters impact the performance** greatly.

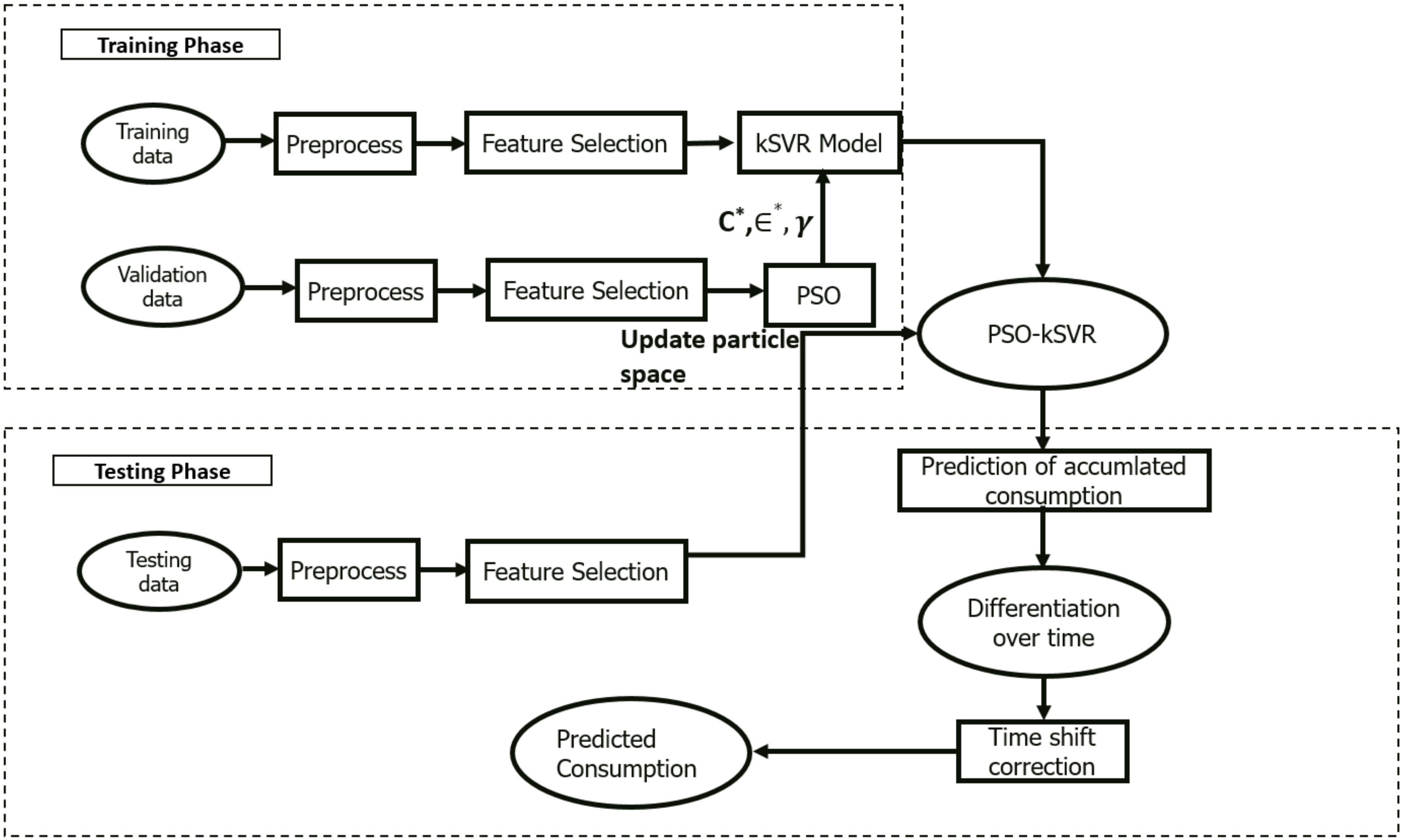


Motivation (contd.)

- Contribution of our work:
  - Best of our knowledge, an ML-based (**PSO-kSVR**) forecasting system using **accumulated consumption data** acquired from **customer's side** to predict thermal energy consumption on the household level: **First Time**.
  - Formulation of PSO-kSVR model to deal with the non-linearity present in data inherently.

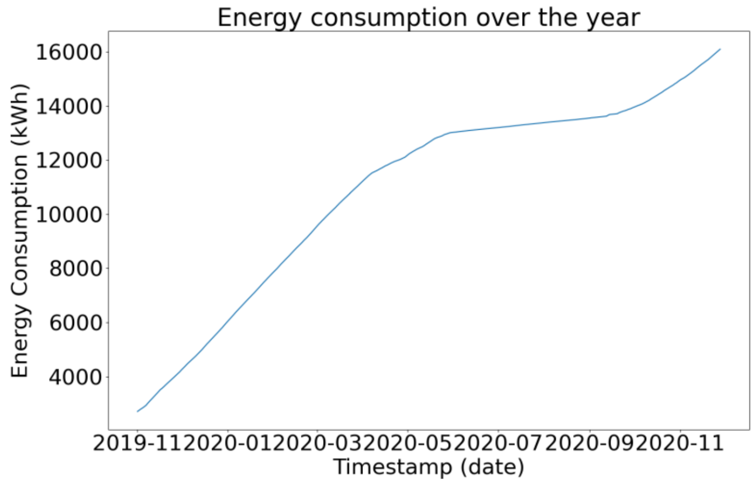


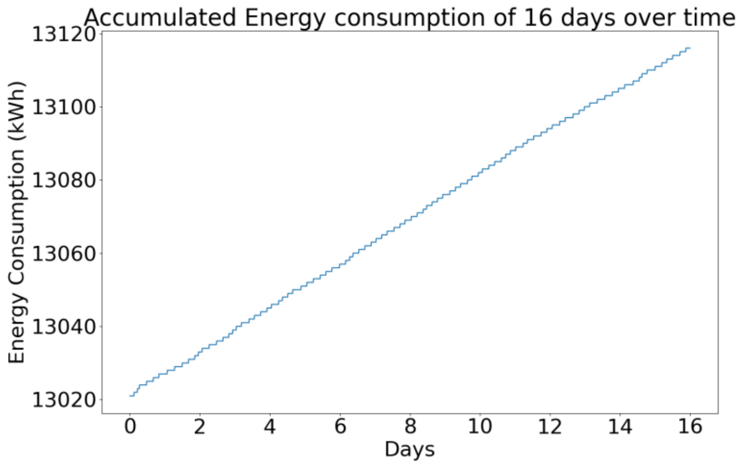
Method Overview



Experiment and Result

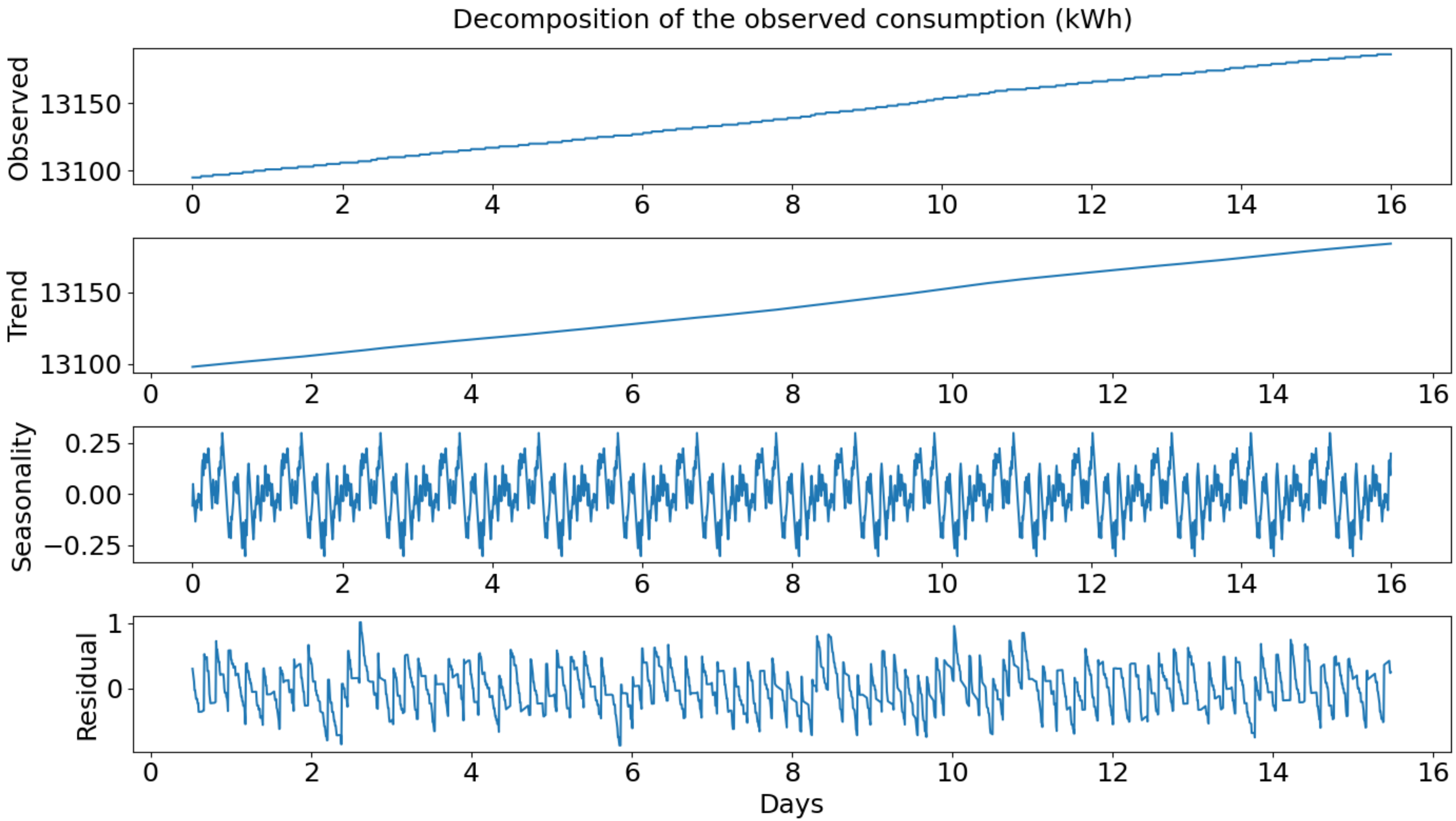
- Used data:
  - **Accumulated heat consumption smart-meter data** from household level in a municipality of Denmark.
  - Weather data of the same municipality (external **feel-like** temperature).





Experiment and Result (contd.)

- Used data:

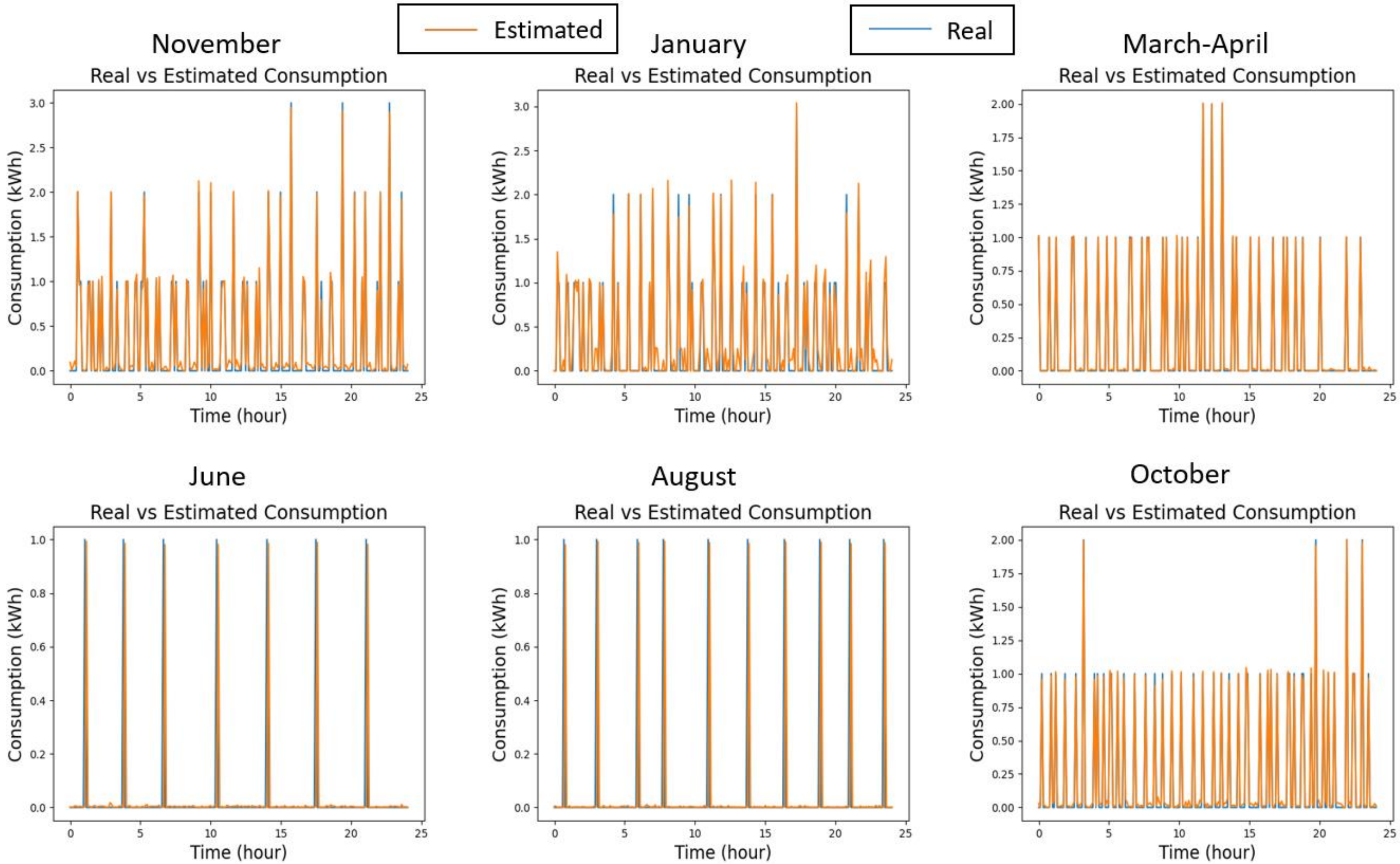


Experiment and Result (contd.)

- **Two types of experiments** have been carried out:
  - **Type I: Meter-specific** level forecasting (for all seasons in a year).
  - **Type II: Societal consumption** forecasting from summed up consumption of a group of meters (for all months in a year).
- **Extracted features** (selected by correlation analysis):
  - Historical accumulated consumption of 1 hour lag
  - External feel-like temperature of 1 hour lag.
- **Train-test-validation** split ratio: **14:1:1**
- Qualitative (how well the predicted data fits the ground truth visually) and Quantitative evaluation (MAPE%, RMSE).
- The result of Type II experiment is compared with the performance of ARIMA model.

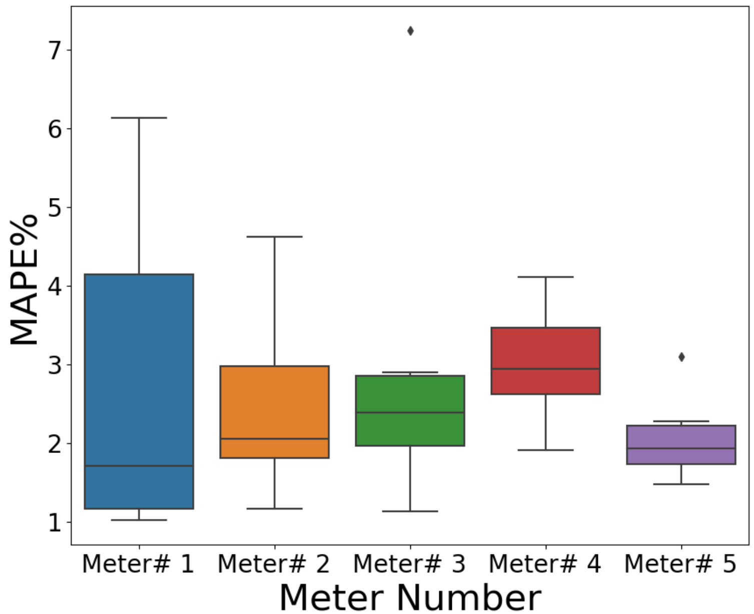
Experiment and Result (contd.)

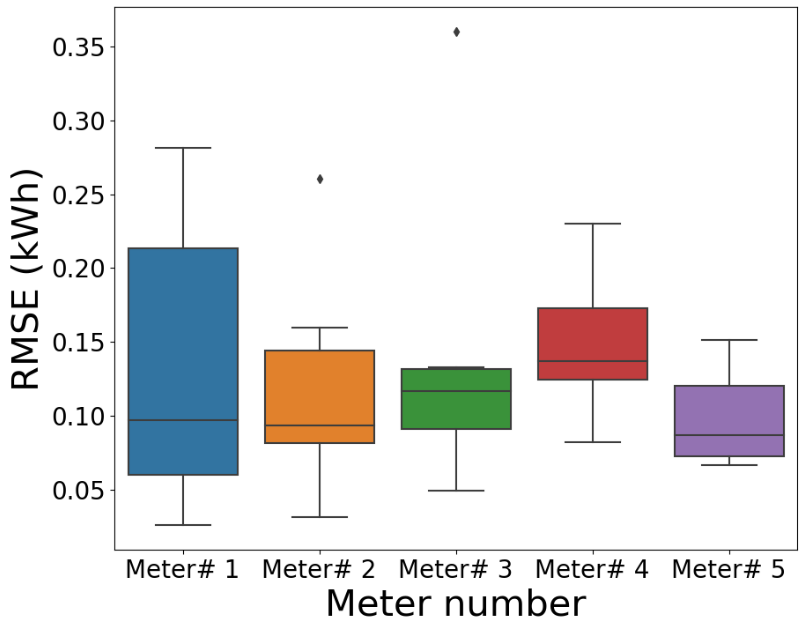
- Result of Type I (Qualitative):



Experiment and Result (contd.)

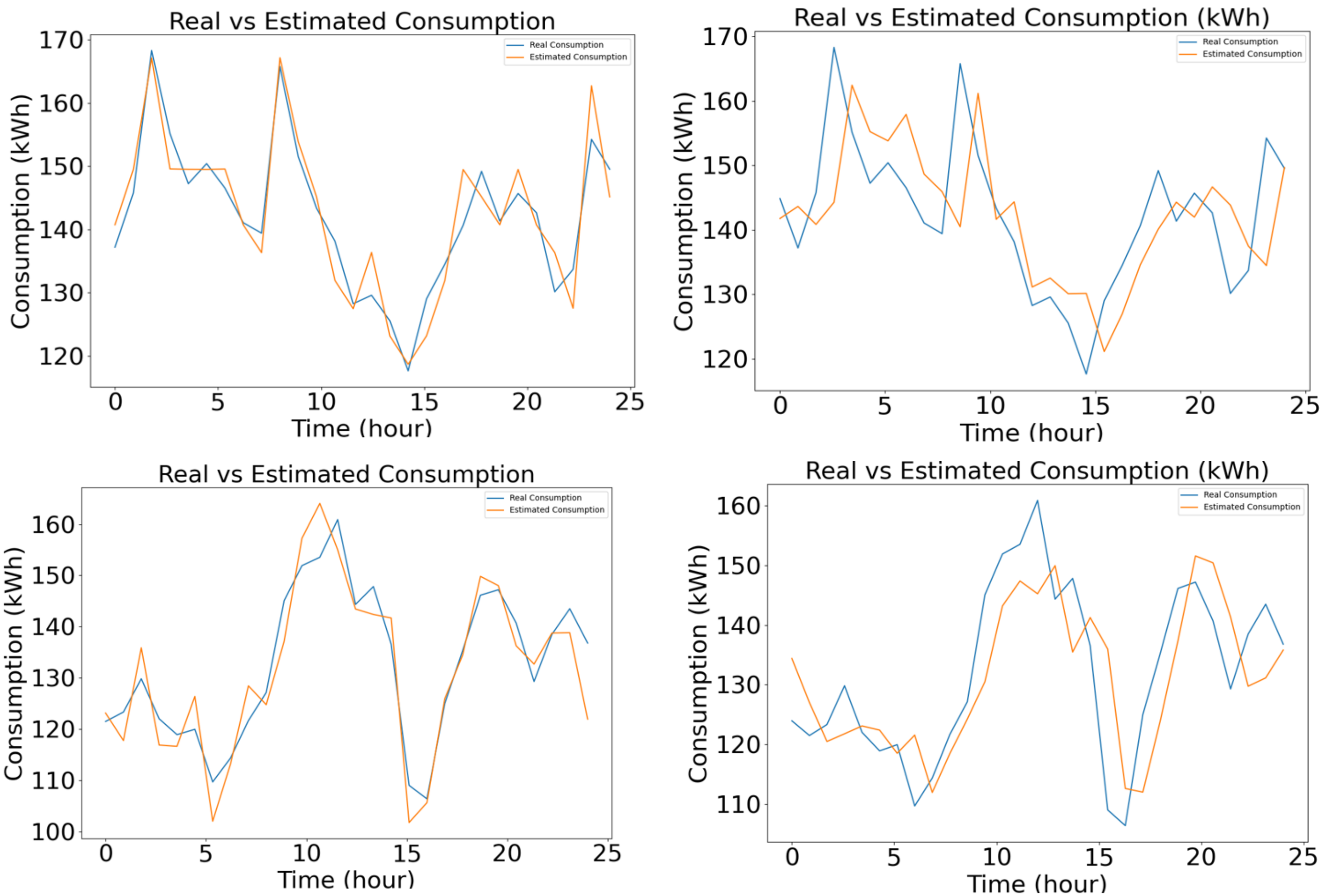
- Result of Type I (Quantitative):
  - Range of mean MAPE: 2.662±0.353%
  - Range of RMSE: 0.1288±0.079 kWh





Experiment and Result (contd.)

- Result of Type II (Qualitative performance comparison):



January

June

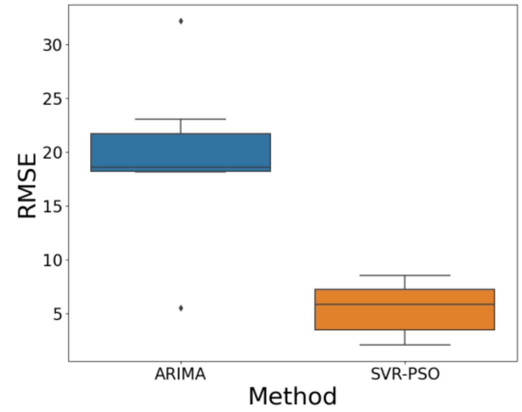
PSO-kSVR

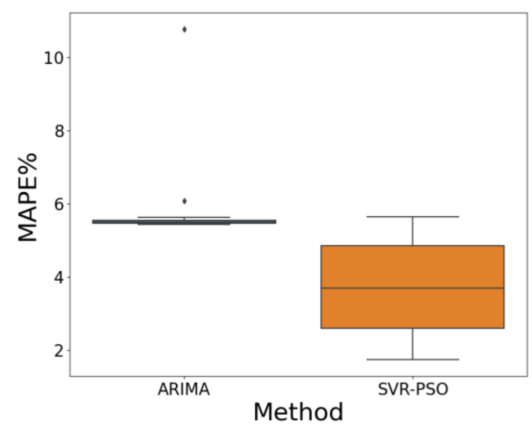
ARIMA

Experiment and Result (contd.)

- Result of Type II (Quantitative performance comparison):
  - 40 datasets comprising of 12 months historical data

Month	ARIMA model		SVR-PSO	
	MAPE%	RMSE	MAPE%	RMSE
November	8.431±2.345	18.884±13.344	**4.079**±1.285	**2.607**±0.527
December	5.546±0.017	22.047±0.266	**3.388**±0.682	**5.467**±0.715
January	5.530±0.033	19.934±1.78	**3.320**±1.128	**5.381**±1.955
February	5.479±0.022	18.256±0.002	**3.448**±1.324	**5.222**±1.910
March	5.486±0.028	18.848±0.584	**4.084**±0.912	**6.268**±1.846
April	5.549±0.021	18.243±0.022	**3.707**±1.206	**5.716**±1.812
May	5.473±0.029	19.354±1.121	**5.114**±0.281	**7.764**±0.545
June	5.540±0.007	18.500±0.22	**2.920**±0.293	**4.890**±0.67
July	5.460±0.028	19.566±0.145	**2.636**±0.899	**4.434**±2.275
August	5.518±0.049	20.637±2.327	**3.951**±1.696	**6.017**±2.547
September	5.441±0.002	20.642±2.41	**4.377**±0.546	**6.852**±0.636
October	5.587±0.042	20.158±1.692	**3.231**±1.348	**5.016**±2.092





Discussion

- Clearly the PSO-kSVR method **outperformed** ARIMA model both quantitatively and qualitatively.
- Usage of accumulated consumption data leads to reduction of expected prediction error by reducing the noise variance in data.
- Non-linear seasonality is modeled using RBF kernel function.

- Limitation:
  - MAPE% is a skewed metric.
  - MAPE% has **asymmetric tendency of penalization**.[12]
  - Problem in calculating MAPE% when ground truth = 0 (Type-I expt.)
  - To deal with division by zero problem, we added the dynamic range of the data as an offset.
  - We had to depend upon RMSE as an additional metric which is more reflective of the performance.

Conclusion and Outlook

- Heat consumption prediction using PSO-kSVR.
  - Hyper-parameter tuning without manual intervention.
  - Promising qualitative and quantitative performance.

- Evaluation from different geographical region is needed.

- Comparison with deep-learning based techniques is required.

- An energy transport model describing individual latency of transport from production plant to household could be combined with the proposed method.

- This combination can lead to a data-driven tool towards optimal thermal energy supply and reduced $CO2$ emission.

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