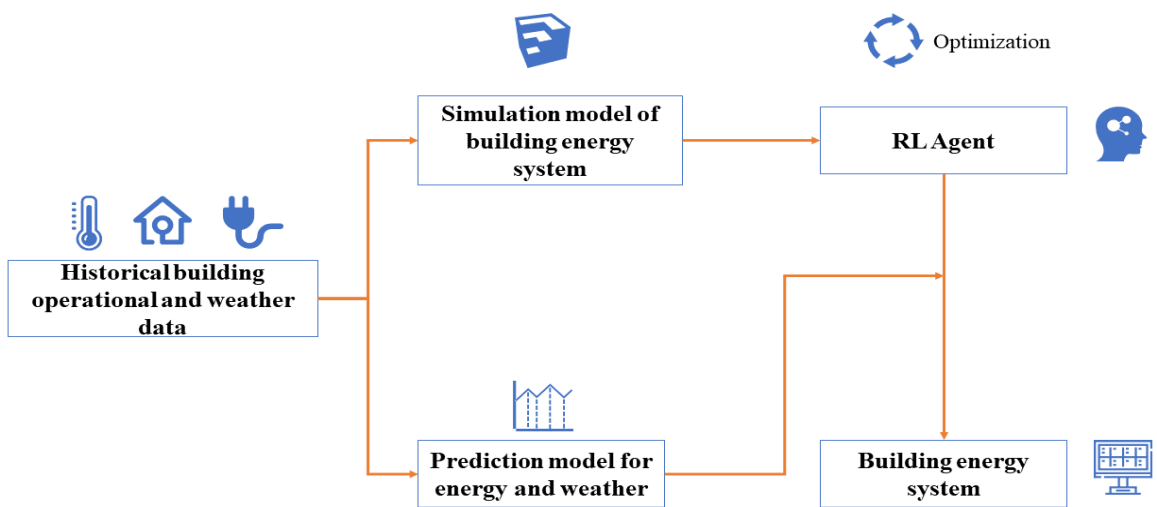


Operation optimization of building energy system based on deep learning and reinforcement learning

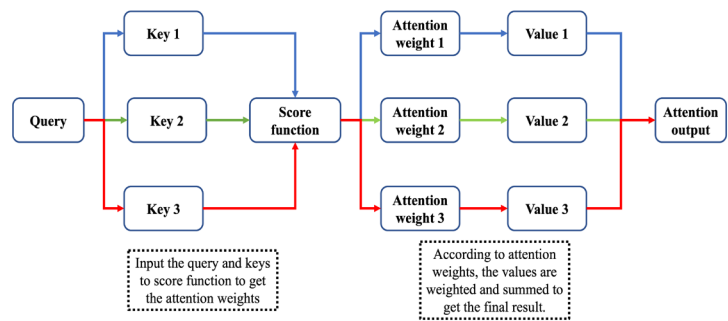
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With the development of urbanization, more than 80% of human activity time is spent in buildings. This change in behavior has led to an increasing proportion of building energy consumption in the total energy. In order to address such a challenge, Japan has taken various measures to reduce 60% to 80% CO2 emissions by 2050 in the field of building energy. An appropriate way to operate the building has a more profound and positive effect on the energy saving. However, since the complexity introduced by human behavior needs to be considered in the operation phase, the research difficulty and energy-saving potential are also higher than design stage. The waste caused by improper energy system control is prevalent, which has a high potential for energy consumption. To optimize the operation of the building energy system, three sub-models are introduced in this research to give a thorough and profound simulation, including simulation environment, prediction model, and optimization algorithms. Firstly, build an accurate prediction model to predict the energy consumption and outdoor weather of future buildings. Based on the predicted results above, the optimization model will use Reinforcement Learning (RL) or Model Predictive Control (MPC) in the entire responsible system. Since prediction and optimization parts involve the most advanced artificial intelligence algorithms, how to efficiently use these algorithms and organically integrate them with the existing knowledge and software in the field of building energy systems will be the focus and difficulty of this research.



The prediction model of this study will predict the time series from two perspectives of time dependence and space dependence. For time dependence, this research mainly uses LSTM model to capture time dependence and adds attention component to obtain interpretable results.

この研究の予測モデルは、時間依存性と空間依存性の2つの観点から時系列を予測します。時間依存性については、この研究では主にLSTMモデルを使用して時間依存性をキャプチャし、注意コンポーネントを追加して解釈可能な結果を取得します。



- 0: Day of year
- 3: Hour
- 6: Penetration
- 9: Water vapor pressure
- 12: Radiation time
- 1: Week of year
- 4: Pressure land
- 7: Temperature
- 10: Humidity
- 13: Cloud cover
- 2: Month
- 5: Pressure sea
- 8: Dew temperature
- 11: Wind speed
- 14: Solar radiation

For spatial dependence, graph neural network is used for processing, and the resulting graph structure can also be used as a result of interpretability.

空間依存性については、グラフニューラルネットワークが処理に使用され、結果のグラフ構造は解釈可能性の結果として使用することもできます。

