Development of a Machine Learning-Based, Dynamic, Granular Grid Outage Forecasting Algorithm

Brookhaven National Laboratory

U.S. DEPARTMENT OF ENERGY

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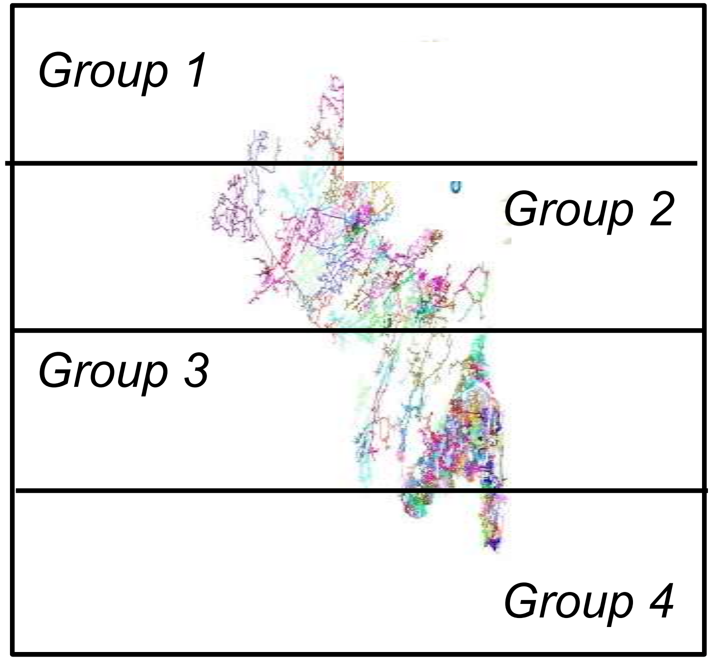
Need for Utility Outage Prediction Models

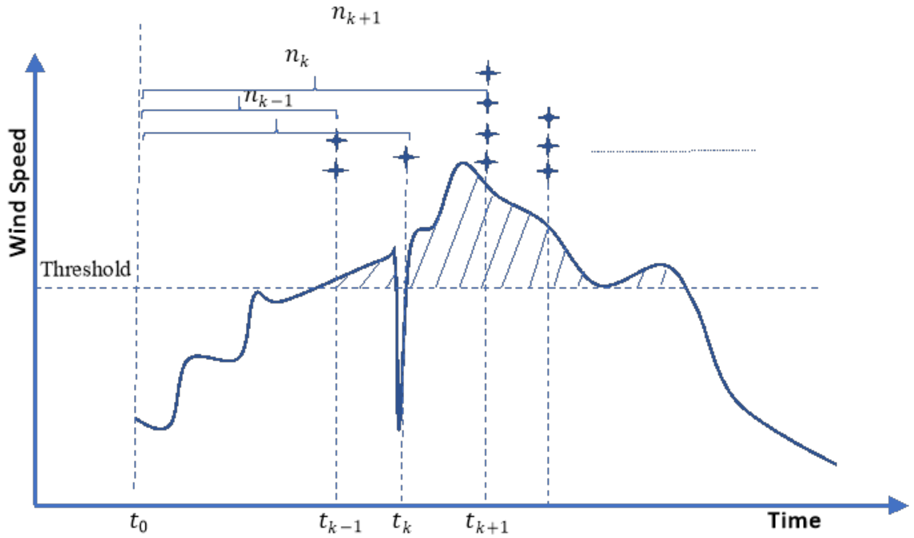
- Utility grid systems are particularly vulnerable to hazardous weather events that are becoming more frequent with climate change.
- Currently available tools for preparation-recovery from hazardous weather events have limited capability
  - Long term planning: Extreme weather impacts often are not considered
  - Recovery: Hindered by untimely, inaccurate and incomplete outage reporting plus a lack of analytic capabilities for estimating/predicting weather impacts
- Need for predictive capability for weather-related damage to the grid
  - Hours – For efficient restoration and recovery
  - Days – For pre-storm preparations
  - Years – For long-term planning of grid infrastructure
- Resiliency includes improved Restoration and Recovery

Data Driven Approach (Dynamic, Granular)

The field has a current focus on data-driven modeling of weather impacts on grid:

- Utility outages information
  - Outages (e.g., Wanik et al. 2015)
  - **Component failures** (Yue et al. 2018 IEEE Trans. Smart Grid)
  - Proxy data (e.g., Satellite nightlights Montoya-Rincon et al. 2022 IEEE Access)
- Weather data
  - Nowcasting – Weather Radar observations (Yue et al 2018)
  - Forecasting - High-resolution weather forecasting models (e.g., Wanik et al. 2015)
  - **Forecasting – Operational weather models** (Zhao et al. 2023 IEEE submitted)
  - Forecasting – Downscaled climate models





Spatial (Grid and Weather) and Temporal (Weather) variability require dynamic and granular approaches

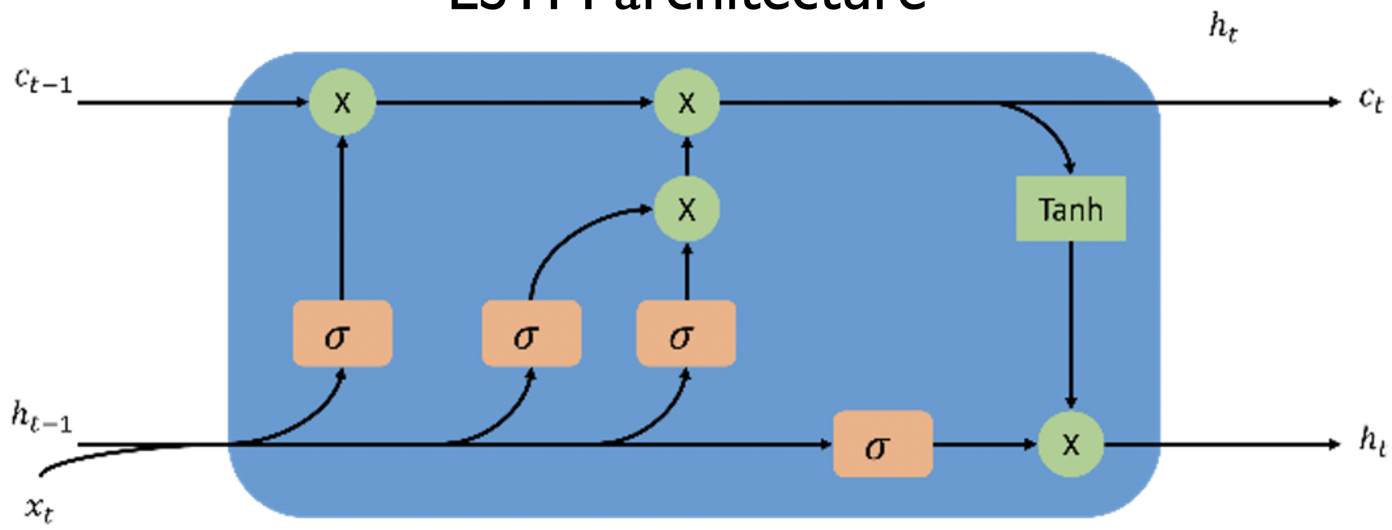
Machine Learning – Long Short -Term Memory

Long Short-Term Memory (LSTM) network is capable of learning long-term dependencies for outage prediction.

Input features (variables)

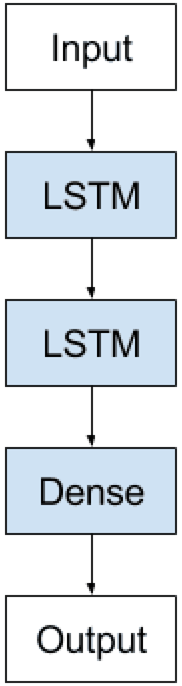
- Inventory data: fixed for each grid
- Weather variables (33) from operational weather forecast models (Winds, Temperature, Soil Moisture, etc.)

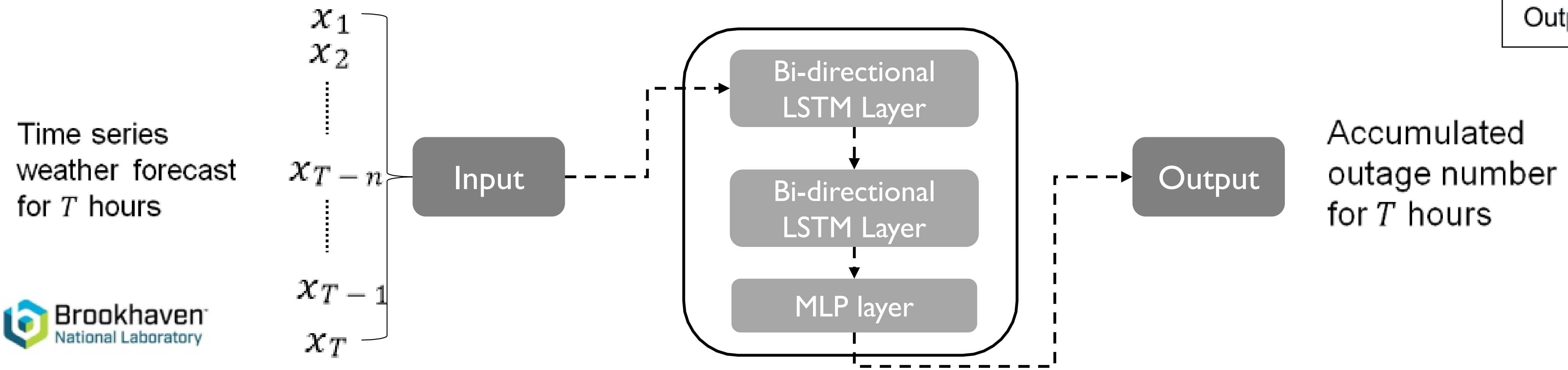
LSTM architecture



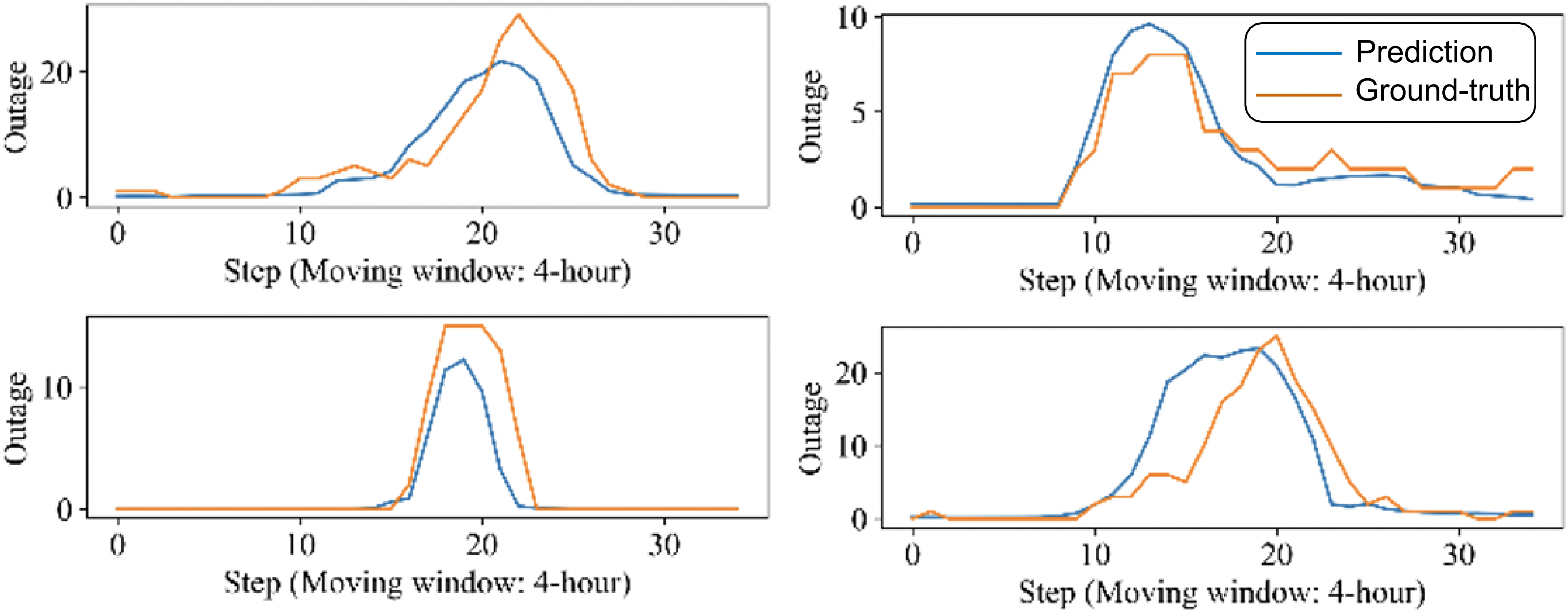
Structure of ML-based Sequential Outage Prediction Model

- Multi-Step LSTM forecasting model
  - Model architecture – A stacked LSTM
    - An extension to an original LSTM including multiple hidden LSTM layers with multiple memory cells, making the model deeper and more accurate
  - Model Input
    - Sequential weather forecasts (selected features) of fixed width, e.g., *T* hours
  - Model Output
    - Predicted accumulated outage number in this period, e.g., of *T* hours.





Case Study I: Model Performance



- LSTM Model trained using 33 weather variables
- Panels are randomly selected from four weather forecasts and four storms
- Model effectively predicts the outage numbers and trends
- Further investigate selection of weather variables and architecture of model

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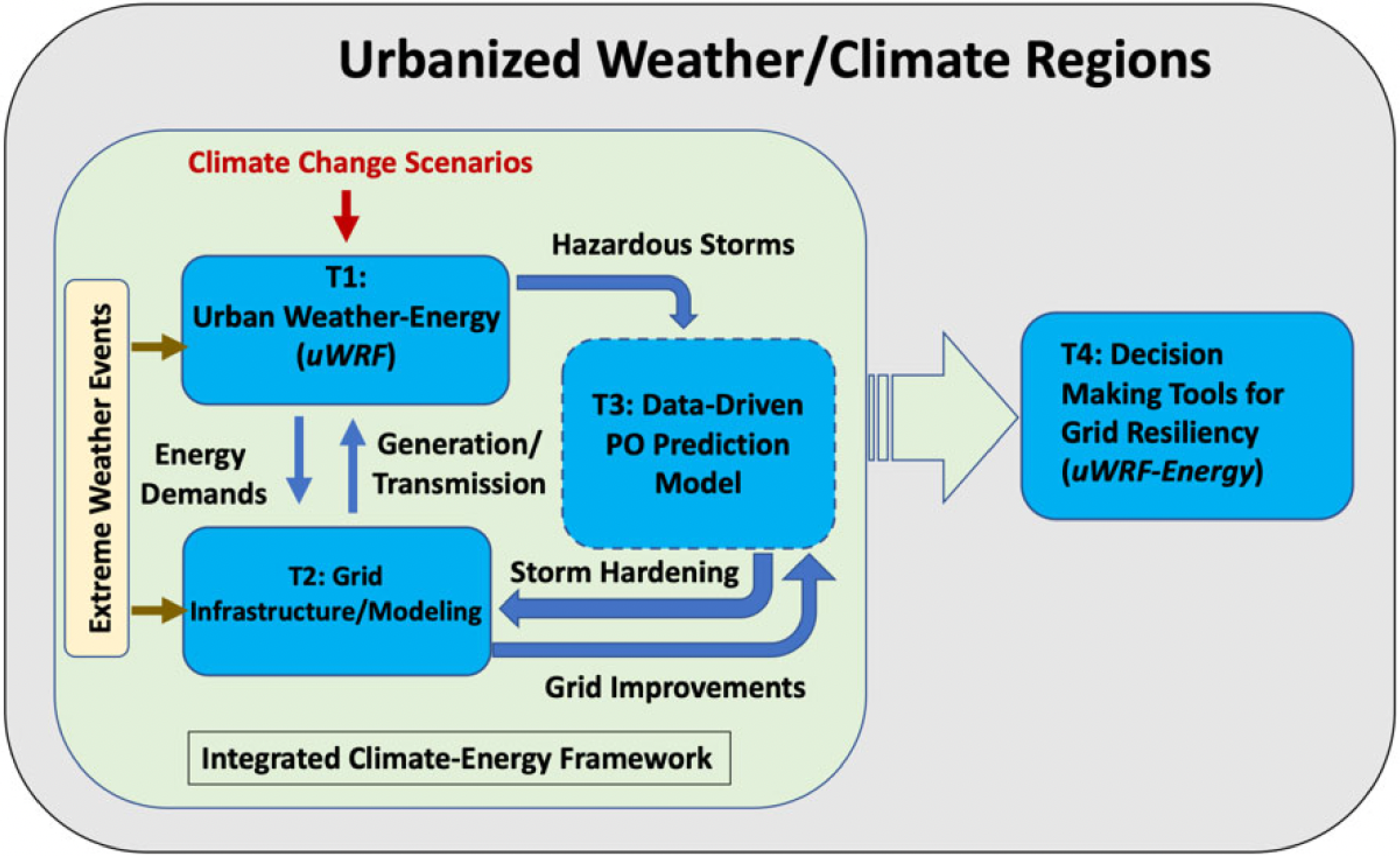
Extending to Climate Scales



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Take Away Messages

- Reliable outage prediction models are an important tool for grid restoration, recovery and resilience
- Most approaches focus on data-driven techniques using historical outage information and weather conditions
- Models have been developed for nowcasting and forecasting to 120-hour lead time with plans for climate scale development
- Newly developed LSTM-based algorithm effectively predicts outages using operational weather forecast model output
- Plans to extend to climate-scale for planning of future grid infrastructure

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