**2. How is it done today? What are the limits of current practice?**

Currently, weather forecasting uses a combination of traditional statistical models and advanced machine learning techniques. Traditional models like ARIMA are commonly used because they can handle linear trends and seasonality in weather data. However, ARIMA struggles with complex, non-linear weather patterns, which limits its effectiveness for short-term and local predictions (Murat et al., 2018; Salman et al., 2018).

Advanced models such as LSTM (Long Short-Term Memory) are becoming more popular because they can capture complex patterns over time, making them more effective for chaotic and non-linear weather predictions (Siami-Namini et al., 2018; De Saa and Ranathunga, 2021). Despite this, LSTM models require significant computational resources and large datasets, which limits their widespread use, particularly in localized forecasting scenarios (Li & Qian, 2018; Salman et al., 2018).

To address the limitations of both methods, hybrid models combining ARIMA and LSTM have been developed. These models take advantage of ARIMA's ability to model linear trends and LSTM’s ability to capture non-linear dependencies, resulting in improved accuracy. Several studies have demonstrated the effectiveness of hybrid ARIMA-LSTM models for weather forecasting, showing their potential to outperform either model when used alone (Salman et al., 2018; Li & Qian, 2018; Abdallah et al., 2020).

References:

- Murat et al., 2018, \*Forecasting Daily Meteorological Time Series Using ARIMA and Regression Models\*

- Salman et al., 2018, \*Weather Forecasting Using Merged Long Short-Term Memory (LSTM) and ARIMA Models\*

- Siami-Namini et al., 2018, \*A Comparison of ARIMA and LSTM in Forecasting Time Series\*

- De Saa and Ranathunga, 2021, \*Comparison between ARIMA and Deep Learning Models for Temperature Forecasting\*

- Li & Qian, 2018, \*Weather Prediction Using CNN-LSTM for Time Series Analysis\*

- Abdallah et al., 2020, \*A Hybrid Methodology for Short Term Temperature Forecasting\*

**3. What’s in our approach? Why will it be successful?**

Our approach involves directly comparing ARIMA and LSTM models for short-term temperature forecasting using a comprehensive dataset of daily temperature records from various U.S. cities. This allows us to assess the strengths of both traditional statistical methods and modern deep learning techniques. ARIMA is well-suited for capturing linear trends and seasonal patterns in weather data, while LSTM excels in modeling non-linear, complex temporal dependencies (Murat et al., 2018; De Saa and Ranathunga, 2021).

We believe this approach will be successful because of the extensive historical data available, which will enable thorough training and testing of both models. Furthermore, by comparing both methods on the same dataset, we can determine which model performs best under different conditions (Siami-Namini et al., 2018). Additionally, we plan to investigate a hybrid ARIMA-LSTM model, inspired by the work of Salman et al. (2018), which showed that merging these models could significantly improve prediction accuracy compared to using either one alone.

The hybrid approach, which leverages ARIMA’s strength in capturing linear trends and LSTM’s capacity to handle non-linear patterns, has been shown to outperform standalone models in various studies (Salman et al., 2018; Abdallah et al., 2020). Combining these methods allows us to exploit their respective strengths, providing a more accurate and robust forecasting solution, particularly for short-term temperature predictions.

Papers to Reference:

1. \*\*Salman et al., 2018\*\* – Demonstrated that combining ARIMA and LSTM models improves accuracy for weather forecasting by leveraging their complementary strengths.

2. \*\*Siami-Namini et al., 2018\*\* – Showed that LSTM significantly reduces prediction errors in time series forecasting, making it a suitable candidate for temperature predictions.

3. \*\*De Saa and Ranathunga, 2021\*\* – Highlighted the limitations of ARIMA for non-linear data and showed the advantages of using LSTM models for weather data.

4. \*\*Murat et al., 2018\*\* – Discussed ARIMA’s ability to capture linear trends in weather data but noted its limitations in handling complex patterns.

5. \*\*Abdallah et al., 2020\*\* – Explored the hybrid ARIMA-LSTM approach, confirming its superiority over standalone models for short-term weather forecasting.

**4. What are the effects, who cares?**

This research on short-term temperature forecasting has a broad impact across several sectors. While meteorologists and climate scientists are direct beneficiaries, other industries rely heavily on accurate temperature forecasts.

In the energy sector, power companies use these forecasts to manage supply and demand, ensuring that they can handle energy usage spikes during extreme weather conditions (Siami-Namini et al., 2018; Salman et al., 2018). Accurate temperature forecasts help farmers make informed decisions about planting, harvesting, and irrigation, which can increase crop yields and reduce losses due to unpredictable weather changes (De Saa & Ranathunga, 2021; Murat et al., 2018).

For the transportation industry, particularly aviation, reliable weather predictions are essential for flight safety and scheduling, allowing airlines to avoid hazardous conditions and reduce delays (Salman et al., 2018). Local governments also depend on precise weather forecasts for emergency preparedness and disaster response, enabling more effective resource allocation in extreme weather events (Murat et al., 2018).

Moreover, sectors such as construction and retail benefit from accurate forecasts, allowing them to plan activities and manage inventories based on expected weather conditions, reducing operational disruptions and financial losses (Abdallah et al., 2020; Ding, 2020). Finally, improving temperature forecasting can lead to better public safety, resource management, and cost savings across a wide range of industries (Li & Qian, 2018; Nghiem et al., 2021).

Papers to Reference:

1. \*\*Siami-Namini et al., 2018\*\* – Discussed the importance of accurate forecasts for energy management and balancing supply-demand during extreme weather.

2. \*\*De Saa & Ranathunga, 2021\*\* – Highlighted the impact of temperature forecasts on agriculture, helping farmers with planting and harvesting decisions.

3. \*\*Salman et al., 2018\*\* – Showed the importance of weather forecasts in aviation, contributing to flight safety and schedule optimization.

4. \*\*Murat et al., 2018\*\* – Emphasized the role of accurate forecasts for local government disaster preparedness.

5. \*\*Abdallah et al., 2020\*\* – Demonstrated the value of weather forecasts for industries like construction and retail in minimizing operational disruptions.

6. \*\*Ding, 2020\*\* – Discussed the application of hybrid models like CNN-LSTM for time series predictions in various industries.

7. \*\*Li & Qian, 2018\*\* – Provided evidence of CNN-LSTM models improving forecast accuracy, relevant for sectors relying on precise weather forecasts.

8. \*\*Nghiem et al., 2021\*\* – Explored advanced hybrid models that can improve prediction accuracy across multiple sectors, contributing to resource management and public safety.

**6. What are the risks and payoffs?**

The main risks of this project stem from the computational demands of LSTM models and the potential for overfitting. (Salman et al. (2018)) highlight the complexity of running LSTM models, especially when dealing with large datasets, which can require significant computational resources. (Siami-Namini et al. (2018)) further note that LSTM models may overfit when trained on limited or low-quality datasets, leading to inaccurate predictions. Additionally, there is the risk that our models may not generalize well across different geographic regions or time periods, limiting the broader applicability of the findings (De Saa & Ranathunga, 2021).

ARIMA, while simpler to implement and computationally less demanding, struggles with non-linear and complex patterns in weather data (De Saa & Ranathunga, 2021; Murat et al., 2018). This could lead to limitations in ARIMA’s effectiveness for short-term temperature forecasting, especially in rapidly changing or chaotic weather conditions.

However, the potential payoffs are substantial. By improving the accuracy of short-term temperature forecasts, this project could benefit industries such as agriculture, where better forecasts help with planting and harvesting (De Saa & Ranathunga, 2021), and the energy sector, which can better manage supply and demand during extreme weather conditions (Siami-Namini et al., 2018; Salman et al., 2018). (Salman et al. (2018)) demonstrated that combining ARIMA and LSTM models can yield more accurate results than using either method alone, which suggests a strong payoff if the hybrid approach is successful.

In addition, clarifying the strengths and weaknesses of ARIMA and LSTM will contribute to the development of more robust forecasting models. (Siami-Namini et al. (2018)) found that LSTM significantly reduces forecasting errors compared to ARIMA, indicating that this project could lead to advances in weather prediction techniques and practical applications, especially if we successfully integrate the strengths of both models (Abdallah et al., 2020).

Papers to Reference:

1. \*\*Salman et al., 2018\*\* – Highlighted the computational complexity of LSTM and the benefits of combining ARIMA and LSTM for improved accuracy.

2. \*\*Siami-Namini et al., 2018\*\* – Addressed the risk of overfitting in LSTM models and demonstrated the error reduction capabilities of LSTM compared to ARIMA.

3. \*\*De Saa & Ranathunga, 2021\*\* – Emphasized the ease of using ARIMA but noted its limitations in handling complex weather patterns.

4. \*\*Murat et al., 2018\*\* – Discussed the limitations of ARIMA in non-linear scenarios, contributing to the risks of using traditional models.

5. \*\*Abdallah et al., 2020\*\* – Provided insights into the hybrid ARIMA-LSTM approach, which could lead to improved forecasting models.