Energy-Adaptive Real-time Sensing for Batteryless Devices

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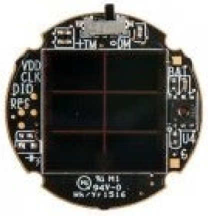
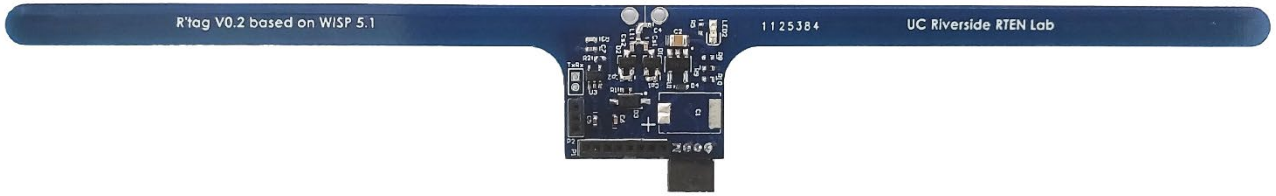
Batteryless Devices

- **Definition:** Devices that do not use battery and are usually powered by intermittent power sources such as sunlight, heat, vibration, and radio signals.
- **Applications**: Smart homes, agriculture, health monitoring, …
- **Advantages**:
  - Few maintenance is required
  - They can last for decades
  - They can be deployed in extreme environments
- **Examples** : Beacon, R’tag, Flicker, ...





Previous work on Task Scheduling on Batteryless Devices

Static methods:

- Target periodic task execution with known charging behavior and try to meet deadlines for real-time tasks[1,2]

Reactive methods:

- Try to schedule tasks of a given taskset when the system is provided with an assumed amount of energy supply [3,4]

[1] M. Karimi, H. Choi, Y. Wang, Y. Xiang, and H. Kim, “Real-Time Task Scheduling on Intermittently Powered Batteryless Devices,” IEEE Internet of Things Journal, vol. 8, 2021.

[2] B. Islam and S. Nirjon, “Scheduling computational and energy harvesting tasks in deadline-aware intermittent systems,” in IEEE Real-Time and Embedded Technology and Applications Symposium (RTAS), 2020.

[3] K. S. Yildirim, A. Y. Majid, D. Patoukas, K. Schaper, P. Pawelczak, and J. Hester, “InK: Reactive Kernel for Tiny Batteryless Sensors,” in SenSys, 2018

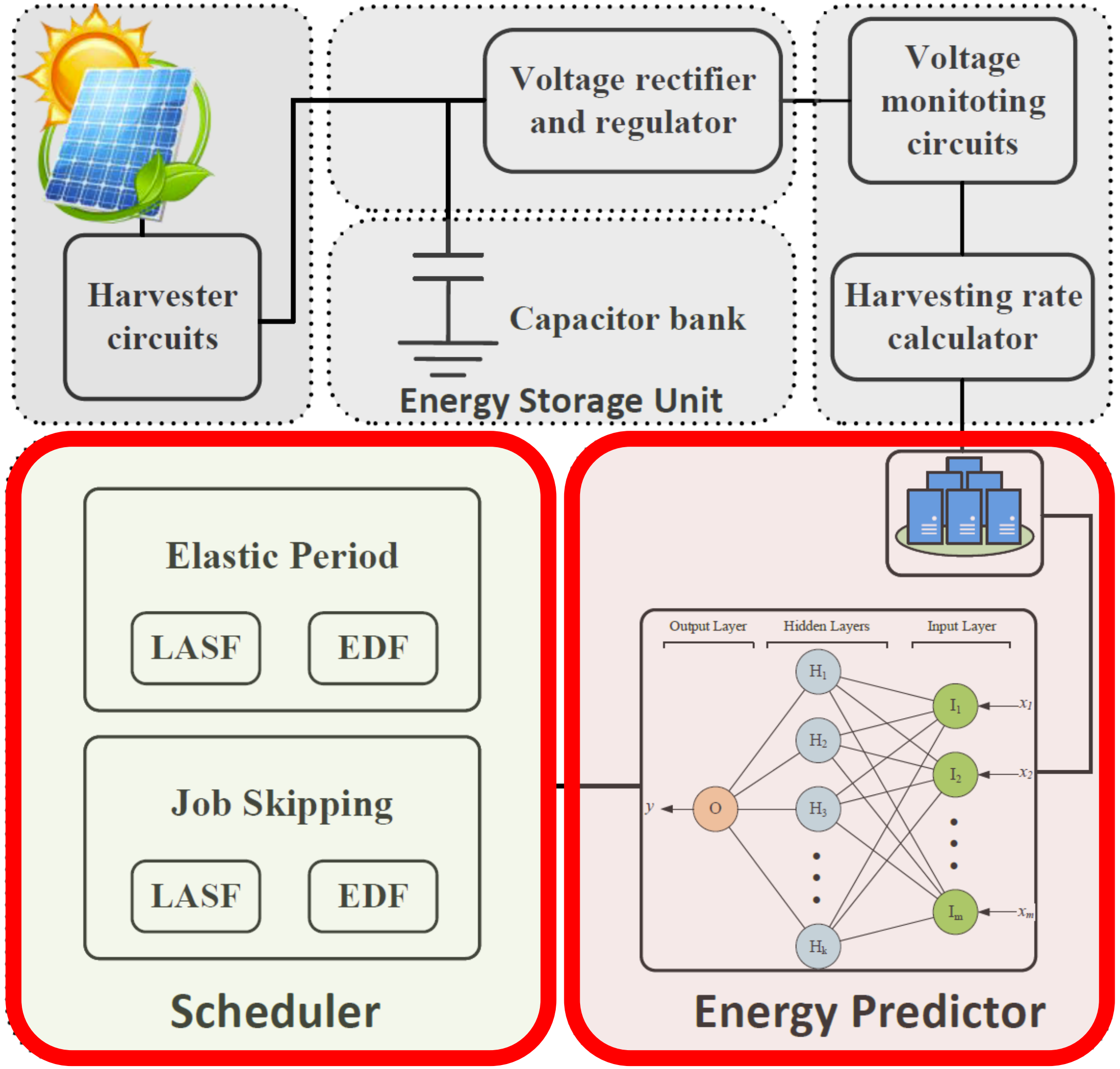
[4] K. Maeng and B. Lucia, “Adaptive low-overhead scheduling for periodic and reactive intermittent execution,” in PLDI, 2020.

Limitations of Previous work

- Unreliable energy source
  - The energy pattern needs to be known a priori
  - The schedule does not adapt to the power reception rate
- In many sensing applications, **data freshness** of tasks is often more important than increasing the number of executed jobs or reducing the number deadline misses.
  - Example: Health monitoring systems
    - Blood sugar monitoring system

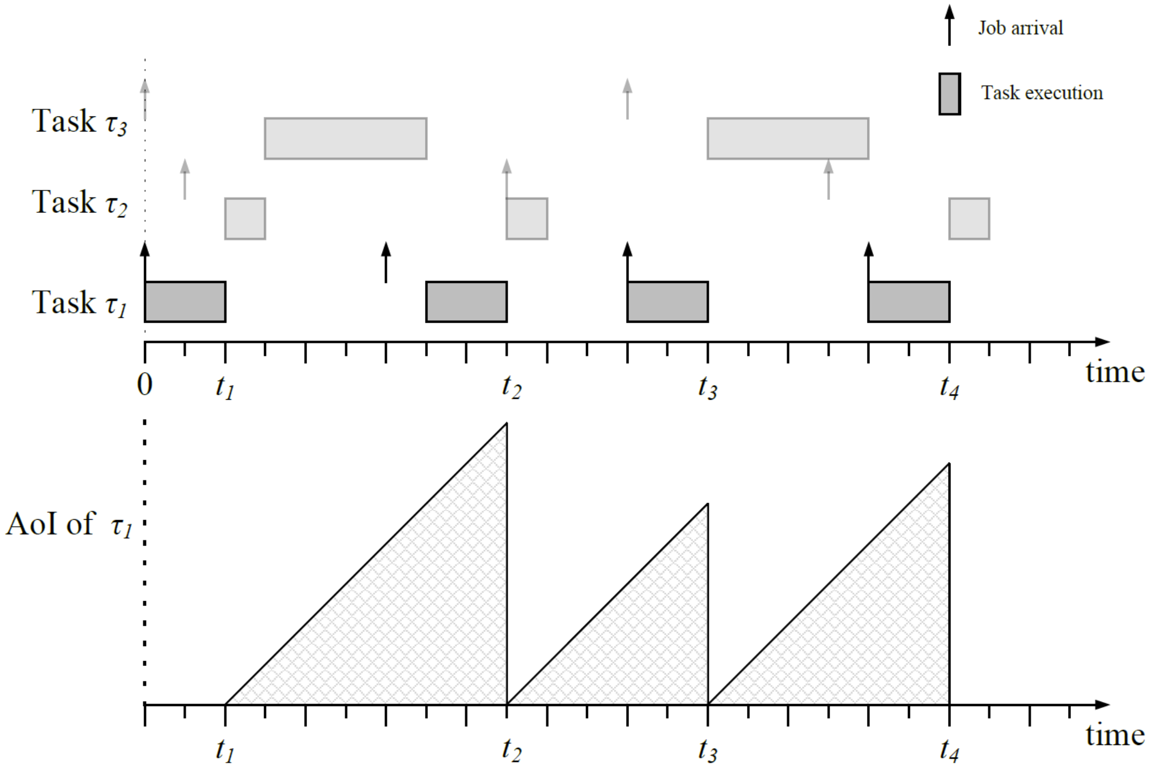
Proposed Framework

- Energy harvester
- Energy storage and regulator units
- Voltage and harvesting rate monitoring
- Energy Predictor
- Scheduler
  - LASF
    - Job Skipping
    - Elastic Period
  - EDF
    - Job Skipping
    - Elastic Period



Data Freshness and Age of Information (AoI)

- AoI of a task τ_i at time t, $A_i(t)$, is the time elapsed since the latest output of the task was generated.



Average AoI of task τ_1

$$\mu_{A_1} = \frac{\int_{t_1}^{t_4} A_1(t)\, dt}{t_4 - t_1} = \frac{\sum_{i=1}^{3}(t_{i+1} - t_i)^2}{2 \times (t_4 - t_1)}$$

Task Model

- Task model
  - C_i: Execution time
  - T_i: Period
  - D_i: Relative deadline
  - MTA_i : Maximum tolerable age of information
  - Tasks are non preemptive

$$\tau_i = (C_i, T_i, D_i, MTA_i)$$

$$\forall i \leq n \mid MTA_i \geq T_i \wedge D_i \leq T_i.$$

- Charging model [1]
  - m_a: Charging rate of the system
  - m_{Pi}: Discharging rate of the task τ_i
  - Q_i: Charging time required before starting the task τ_i

$$Q_i = \frac{(m_{Pi} - m_a) \times C_i}{m_a}$$

[1] M. Karimi, H. Choi, Y. Wang, Y. Xiang, and H. Kim, “Real-Time Task Scheduling on Intermittently Powered Batteryless Devices,” IEEE Internet of Things Journal, vol. 8, 2021.

Task Scheduling with energy constraint

- Earliest Deadline First (EDF) scheduling with energy constraint

$$\boxed{Q_i^+ = max\{Q_i, 0\}}$$

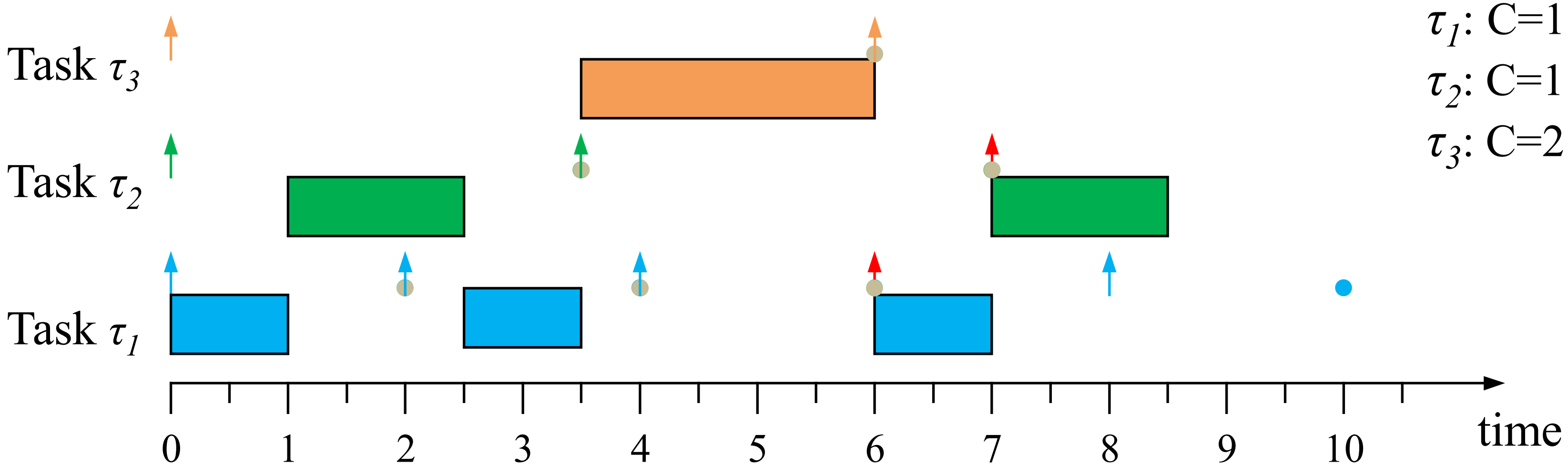
$$\boxed{\text{Blocking time: } B_k = \max_{j:D_j > D_k} C_j}$$

$$\forall i, j \le n, i \le j \rightarrow D_i \le D_j \xrightarrow{\text{Schedulable if}} \forall k = 1, ..., n, \quad \sum_{i=1}^{k} \left(\frac{C_i + Q_i^+}{D_i} \right) + \frac{B_k}{D_k} \le 1$$

  - Relative deadlines no larger than period $\forall i = 1, ..., n, \quad D_i \le T_i$
  - Unpredictable behavior in overload or underload situation (decrease or increase in charging rate)

Task Scheduling with energy constraint

- Earliest Deadline First (EDF) scheduling with energy constraint and overload management
  - Elastic Period $$U_e = \max_{k \le n} \left\{ \sum_{i=1}^{k} \left(\frac{C_i + Q_i^+}{T_i} \right) + \frac{B_k}{T_k} \right\} \longrightarrow T_i' = T_i \times U_e$$
  - Job skipping: Skip jobs if the previous job of the same task has not finished its execution



τ_1: C=1, T=2, D=2
τ_2: C=1.5, T=3.5, D=3.5
τ_3: C=2.5, T=6, D=6

LASF Task Scheduler

- Least AoI Slack First (LASF)

$$U_l = \max_{k \le n} \left\{ \sum_{i=1}^{k} \left(\frac{C_i + Q_i^+}{MTA_i} \right) + \frac{B_k}{MTA_k} \right\}$$

  - Job Skipping
    - Similar to EDF
  - Elastic Period
    - $T_i' = \widehat{MTA}_i$
    - This guarantees each task τ_i to meet its AoI constraint of $\widehat{MTA}_i$

Algorithm 1 Least AoI Slack First

$t \leftarrow$ current time
Update A_i of each task
Compute U_l by (7)
for $k \le n$ **do**
    $\widehat{MTA}_k = U_l \times MTA_k$ ▷ U_l is obtained by (7)
    $ASD_k = \widehat{MTA}_k - C_k$
end for
$h \leftarrow \arg\min_i (ASD_i - A_i)$
if $Curr\_Charge \ge Q_i$ **then**
    Execute the task τ_i
else
    $t_r \leftarrow$ earliest release time of a job from any of the tasks
    $t_c \leftarrow t + Q_i - Curr\_Charge$
    $t_{new} \leftarrow min\{t_c, t_r\}$
    $t \leftarrow t_{new}$ ▷ Device goes to sleep for $t_{new} - t$ seconds
end if

Considerations for Energy Prediction

- Requirements
  - Lightweight due to limited processing capability
  - Relatively accurate
  - No additional sensor information needed
- Previous work
  - EWMA [5] - baseline
  - WCMA [6]
  - Pro-Energy [7] – state of the art

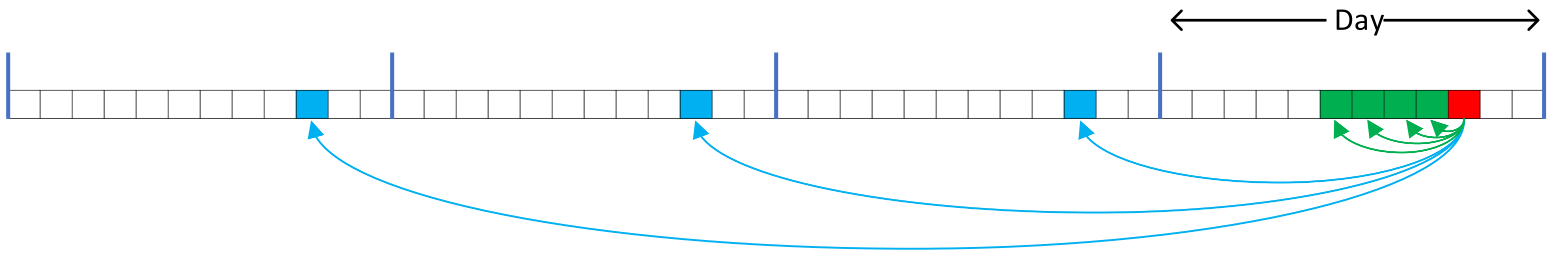
[5] D. K. Noh and K. Kang, “Balanced energy allocation scheme for a solarpowered sensor system and its effects on network-wide performance,” J. Comput. Syst. Sci., vol. 77, no. 5, p. 917–932, Sep. 2011.

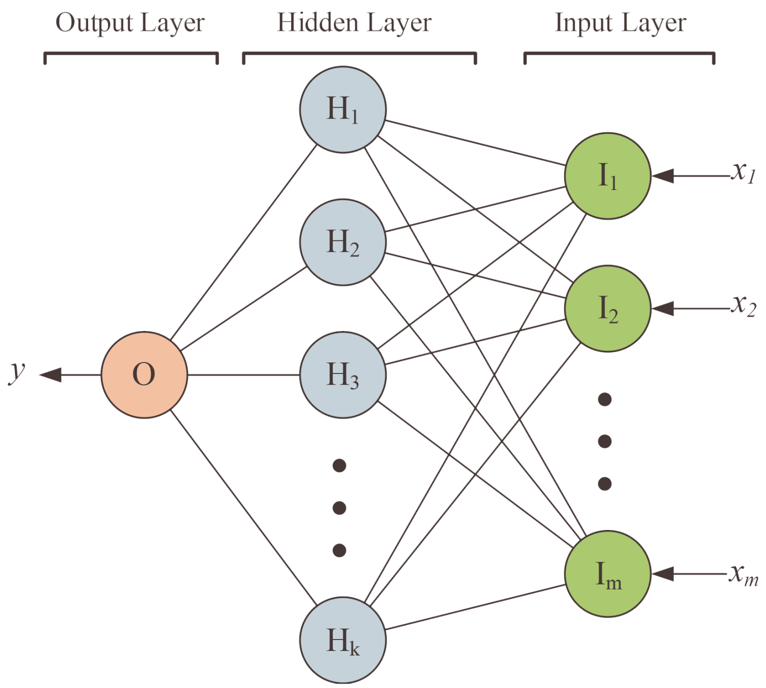
[6] J. Recas Piorno et al, “Prediction and management in energy harvested wireless sensor nodes,” in International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace Electronic Systems Technology, 2009, pp. 6–10.

[7] A. Cammarano et al., “Pro-energy: A novel energy prediction model for solar and wind energy-harvesting wireless sensor networks,” in IEEE International Conference on Mobile Ad-Hoc and Sensor Systems, 2012.

Energy Predictor

- Neural Network Based Predictor
  - The solar radiation of each time slot is relatively correlated to the past few hours of that time slot as well as the same time slot for past few days



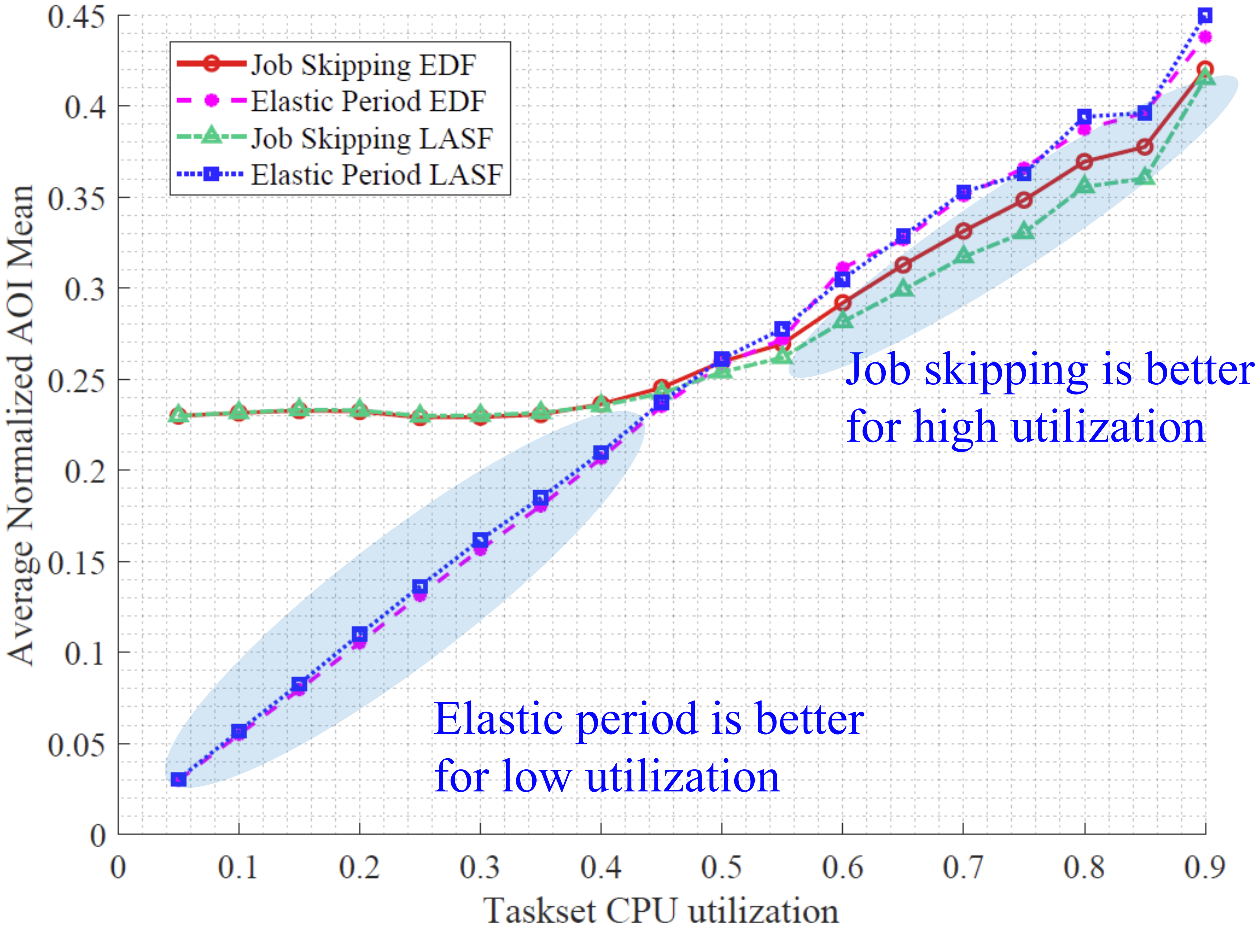


  - Inputs (for 30 minutes time slot):
    - 10 samples from previous time slots (past 5 hours)
    - 4 samples from 4 previous days
  - 12 neurons in hidden layer
  - NREL data set[8]
    - Trained with data from 2017 to 2019

[8] A. M. Andreas, "University of Nevada - Las Vegas," 2006. [Online]. Available: https://midcdmz.nrel.gov/apps/sitehome.pl?site=UNLV

Evaluation: Scheduler Performance

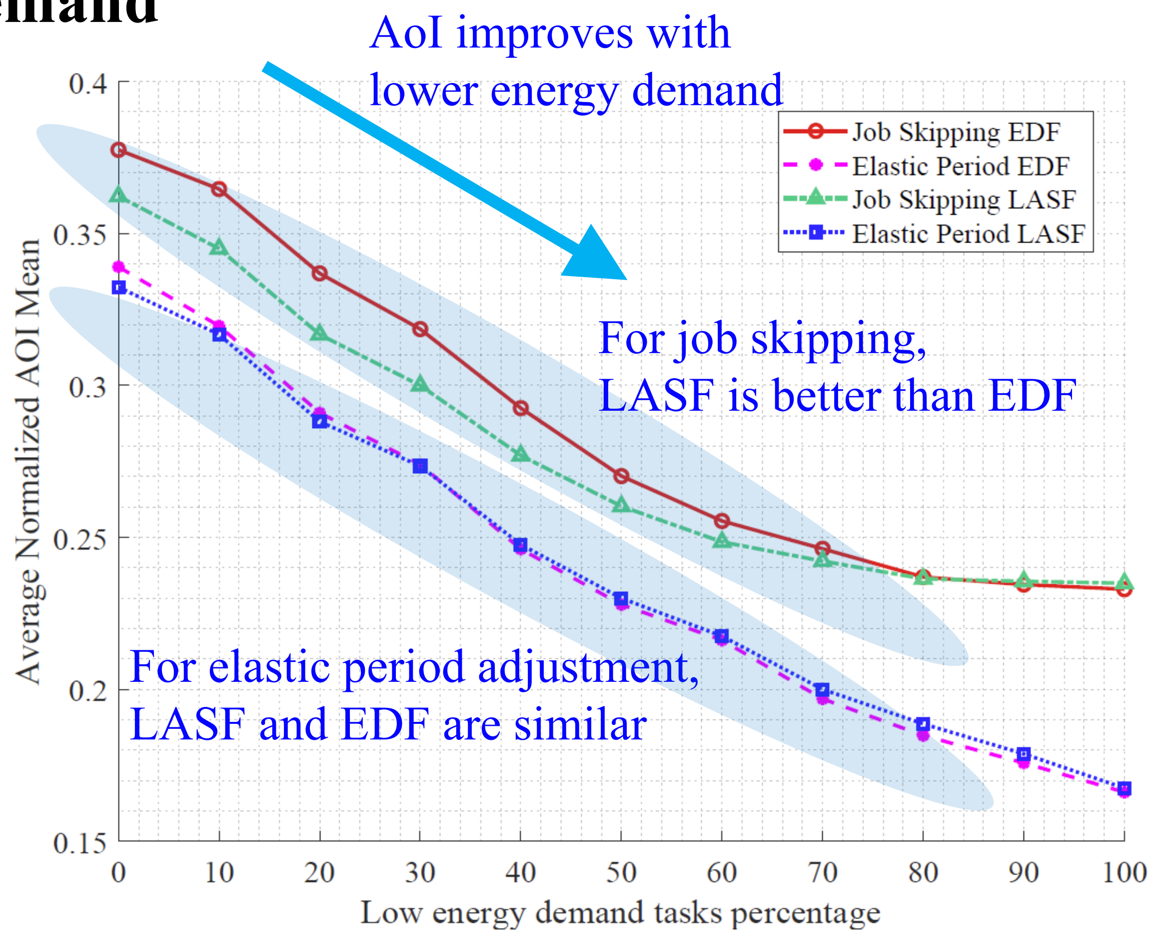
- **Objective: Explore effect of utilization**
  - 1000 tasksets
  - Utilization from 0.05 to 0.9 in 0.05 steps
  - $m_a = 3$
  - UUniFast [9] is used to generate random tasksets
  - Discharging rate of each task are chosen randomly from 2 to 10
  - MTA for each task is chosen randomly from 1x to 4x of its period



[9] E. Bini and G. C. Buttazzo, “Measuring the performance of schedulability tests,” Real-Time Systems, vol. 30, no. 1-2, pp. 129–154, 2005.

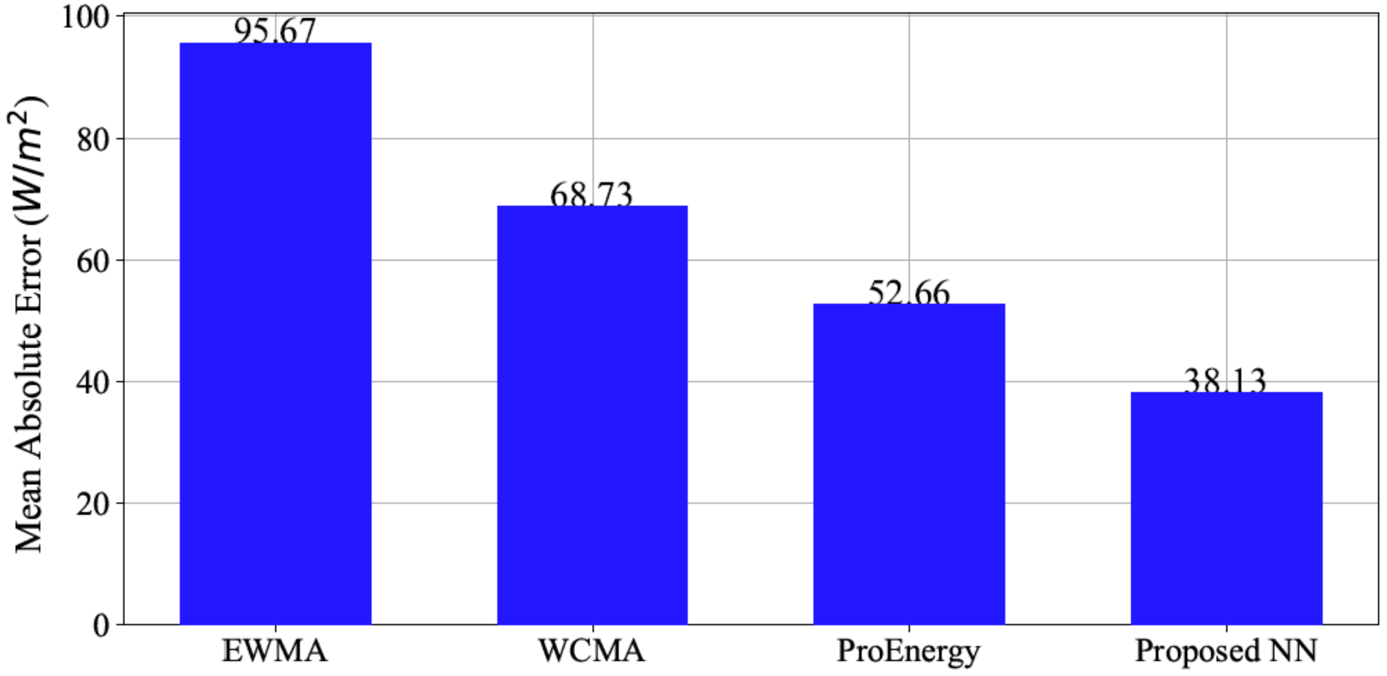
Evaluation: Scheduler Performance

- **Objective: Explore effect of task energy demand**
  - Energy demand task ratio effect
    - High demand tasks: discharging from 8 to 10
    - Low demand tasks: discharging from 1 to 3
    - 1000 tasksets
    - $m_a = 3$
    - UUniFast is used to generate random tasksets
    - MTA for each task is chosen randomly from 1x to 4x of its period



Evaluation: Energy Predictor

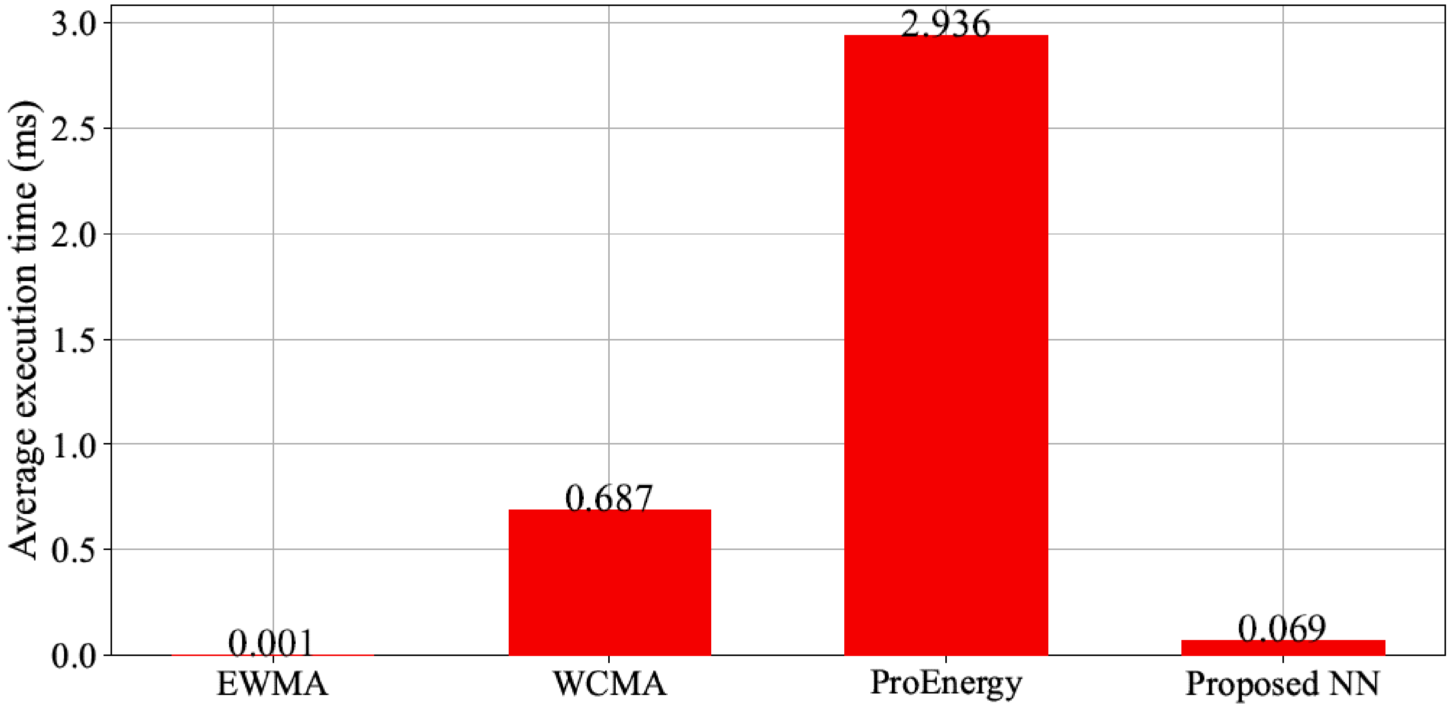
- **Objective: Prediction accuracy**
  - Test set: data for the entire year of 2020
    - NREL data set
    - Evaluation is performed on Raspberry Pi 3



*For reference: average solar energy rate is about 800 to 1200 Watt/m2 at noon

Evaluation: Energy Predictor

- **Objective: Runtime overhead**
  - Test set: data for the entire year of 2020
    - NREL data set
    - Evaluation is performed on Raspberry Pi 3



Conclusion and Future Work

- We presented a new framework for scheduling real-time sensing tasks with data freshness constraints on batteryless devices.
- We proposed a lightweight machine learning based solar energy predictor
- Our proposed predictor outperformed the state-of-the-art methods in terms of mean absolute error as well as runtime overhead
- We studied job skipping and elastic period adjustment methods to deal with overload situations

- The combination of tasks with AoI constraints and hard deadlines can be considered
  - Preprocessing task can be performed before sensing tasks
  - Transmission tasks over low power medium such as BLE can be scheduled after each sensing
- We plan to explore these issues and further evaluate our methods in real-world conditions

Thank You