Towards Optimal Solar Tracking: A Dynamic Programming Approach

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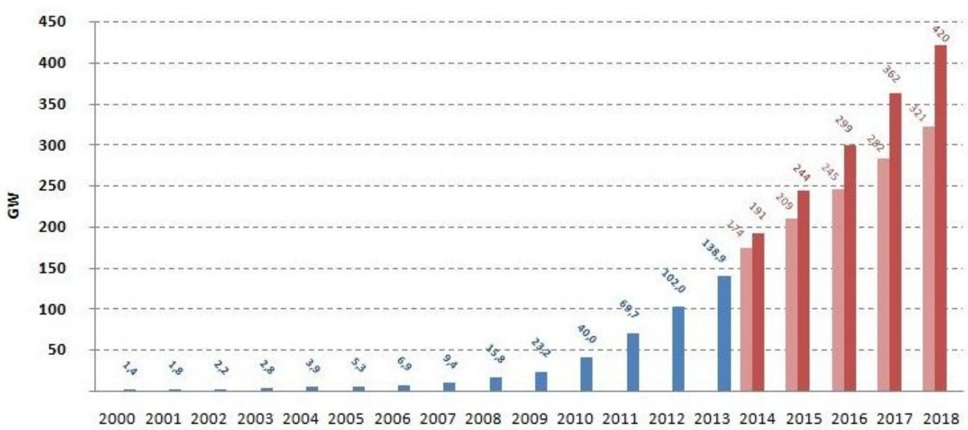
Motivation

- Photovoltaic Systems (PVSs) are being integrated into the Grid

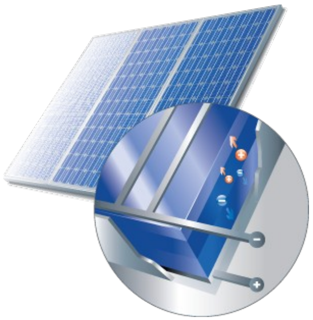
- **~38%** estimated **worldwide growth for 2013**



European Photovoltaic Industry Association 2014

Motivation

- **Increase PVS efficiency**



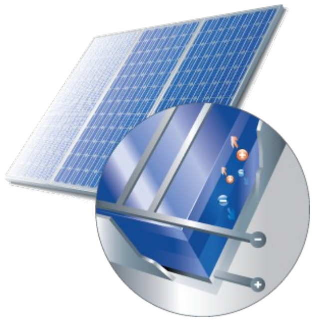
Increase solar cell efficiency

Better PVS location

Solar tracking (ST)

Motivation

➢ **Increase PVS efficiency**



Increase solar cell efficiency

Better PVS location

Solar tracking (ST)

➢ Depending on location and season, ST can increase PVS power output by **up to 100%**

Solar Tracking (ST)

What are the drawbacks of current techniques?

Solar Tracking (ST)

Active
Relies on (electrical) motors

Passive
Relies on thermal (expansion) effects
Less common

Sensor-based
Relies on complex closed-loop controllers and sophisticated instruments

Chronological
Does not consider the forecasted or prevailing weather conditions

Typically, they do not take the energy consumption of the trackers into account

Overview of Main Contributions

- Novel **low-cost predictive** ST:
  - ✓ **No expensive** equipment, sensors or data
  - ✓ Estimates the optimal trajectories **a day before** given weather forecasts
  - ✓ Considers also the **tracking consumption**
  - ✓ First **dynamic programming** approach for ST
  - ✓ Can be used in **both an open-loop or a closed-loop** manner
  - ✓ Comes with **guaranties of optimal or near-optimal performance**
  - ✓ Comes with an **expected PVS power output** estimation

- Propose a **new Policy Iteration approximation algorithm** for ST (STPI):
  - Suitable for **large state-action space MDPs**
  - **First alternating optimization** algorithm for **MDPs**

- Propose a **generic** and **parameterizable** ST consumption model

Overview of Main Contributions

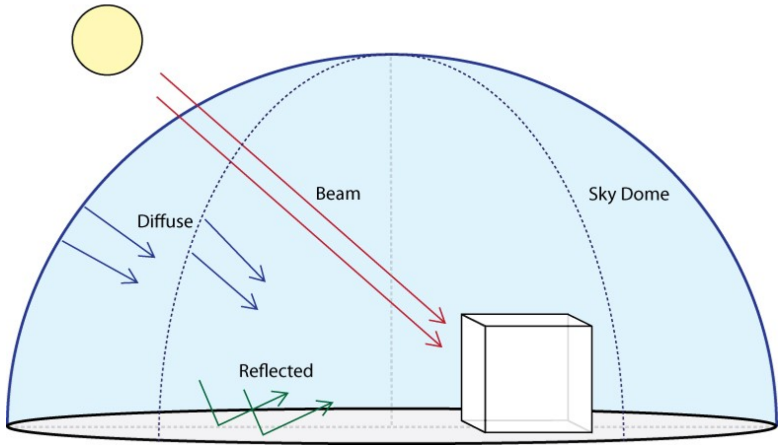
- STPI optimizes on top of a new **Myopic ST** method that we also propose
- STPI and Myopic ST are:
  - ✓ **Applicable** with many ST systems, as e.g.;
    - Azimuth-Altitude Dual Axis Trackers (AADAT)
    - Vertical Single Axis Trackers (VSAT)

      } **used in our Evaluation**
    - Tilted Axis Tracker
    - Horizontal Single axis Tracker
  - ✓ **Expandable** to many others ST systems (e.g., pole trackers)
- Propose a method for any fixed, yet readjustable PVS, within a weather-station region
- Our simulation results show that our approach outperforms all benchmark methods:
  - **Chronological** ST
  - **Sensor-based** ST
  - **Fixed-orientation** Systems

Background Material

Some astronomy...

- The **total irradiance** G_T, falling on an arbitrarily oriented surface, consists of three components:

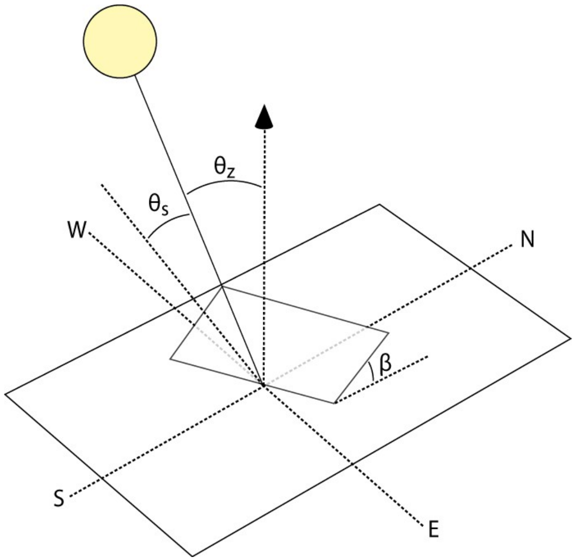


$$G_T = G_B + G_D + G_R$$

Beam $G_B = G_B^{max} \cos\theta_s$

Sky-diffuse $G_D = G_D^{max}(1+\cos\beta)/2$

Ground-reflected $G_R = G_R^{max}(1-\cos\beta)$

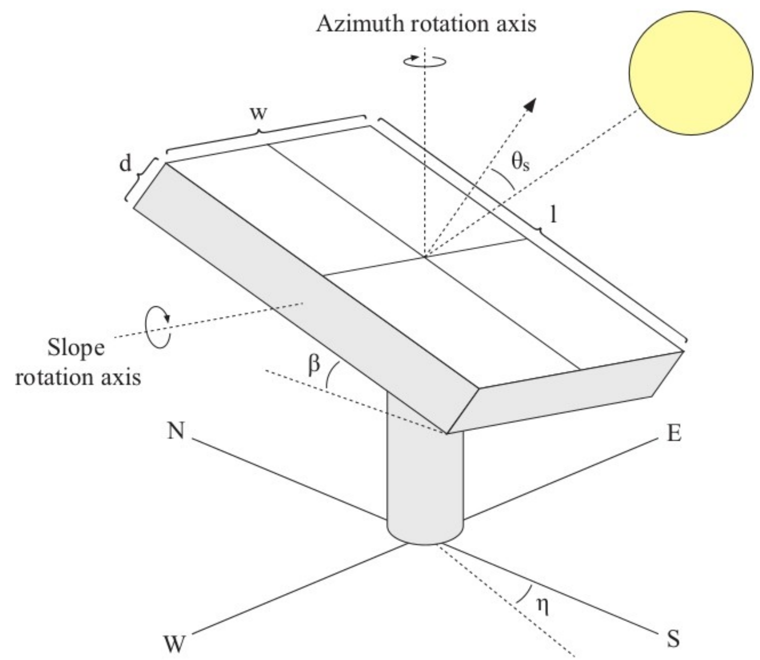


Background Material

ST architectures

➢ **Azimuth-altitude dual axis trackers (AADAT)** and **Vertical single axis trackers (VSAT)**

r_{Az}	Azimuthal angular range
r_{Sl}	Elevation angular range
θ	Step-size (minimum displacement)
K	Set of azimuthal positions $\vert K\vert = \lfloor r_{Az}/\theta \rfloor + 1$
Λ	Set of slope positions $\vert\Lambda\vert = \lfloor r_{Sl}/\theta \rfloor + 1$
δ	Time required for a minimum displacement θ to occur
Δ	Time between two consecutive controller-system interactions $\Delta \geq \delta \cdot max(\vert K\vert - 1, \vert\Lambda\vert - 1)$
Δ_{Day}	Day-length
I	Set of the daily required controller-system interactions $\vert I\vert = \lceil \Delta_{Day}/\Delta \rceil$
τ	Time-step/interaction ID



Abstract AADAT (in VSAT β is fixed)

A. A. Panagopoulos, G. Chalkiadakis, N. R. Jennings "Towards Optimal Solar Tracking: A Dynamic Programming Approach"

A Dynamic Programming Approach

Defining the MDP

- The problem is naturally modeled as a **fully observable, finite-horizon, discrete-time Markov decision process** (MDP)

$$<\boldsymbol{S},\boldsymbol{A},\boldsymbol{R},\boldsymbol{P}>$$

$\boldsymbol{S}$ $\lvert S\rvert \geq \lvert K\rvert \cdot \lvert\Lambda\rvert$	Each $s \in S$ is a $<\kappa_s,\lambda_s,\boldsymbol{w}_s>$ where: ▪ $\kappa_s \in [1,\lvert K\rvert]$ Azimuthal position ▪ $\lambda_s \in [1,\lvert\Lambda\rvert]$ Slope position ▪ $\boldsymbol{w}_s$ Stochastic weather variables vector	$\boldsymbol{R}$	$R_a(s,s')=Prod(s,s')-Cons(s,s')$ $Prod(s,s')=\frac{(Pwr(s)+Pwr(s'))}{2}\Delta$
$\boldsymbol{A}$ $\lvert A\rvert=\lvert K\rvert \cdot \lvert\Lambda\rvert$	Each $a \in A$ is a $<\kappa_a,\lambda_a>$ where: ▪ $\kappa_a \in [1,\lvert K\rvert]$ Azimuthal position ▪ $\lambda_a \in [1,\lvert\Lambda\rvert]$ Slope position	$\boldsymbol{P}$	The transition model defines $P(s,a,s')$ $\kappa_{s'}=\kappa_a \quad \lambda_{s'}=\lambda_a \quad P(\boldsymbol{w}_s'\lvert\boldsymbol{w}_s)$

- $\lvert I\rvert$ The MDP **horizon**

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A Dynamic Programming Approach

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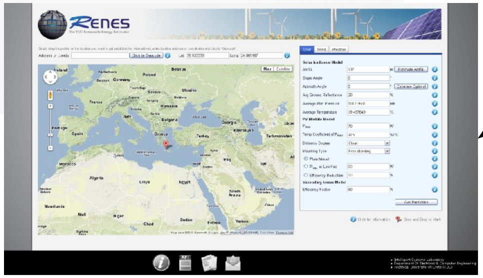


- $\lvert I\rvert$ The MDP **horizon**

Panagopoulos et al. *"Predicting the Power Output of Distributed Renewable Energy Resources within a Broad Geographical Region", ECAI-2012*

A Dynamic Programming Approach

A PV tracker consumption model

- $$Cons(s,s') = \frac{1}{c_{eff}} \left(\sum_{1}^{|\kappa_s - \kappa_{s'}|} Cons_{\theta}^{az} + \sum_{1}^{|\lambda_s - \lambda_{s'}|} Cons_{\theta}^{sl} \right)$$

$$Cons_{\theta}^{az} = \sum_{\mu=1}^{3} \left(\alpha_{\mu} I_{A_{(\theta,\mu)}} - T^{w}_{A_{(\theta,\mu)}} \right) \theta_{\mu}$$

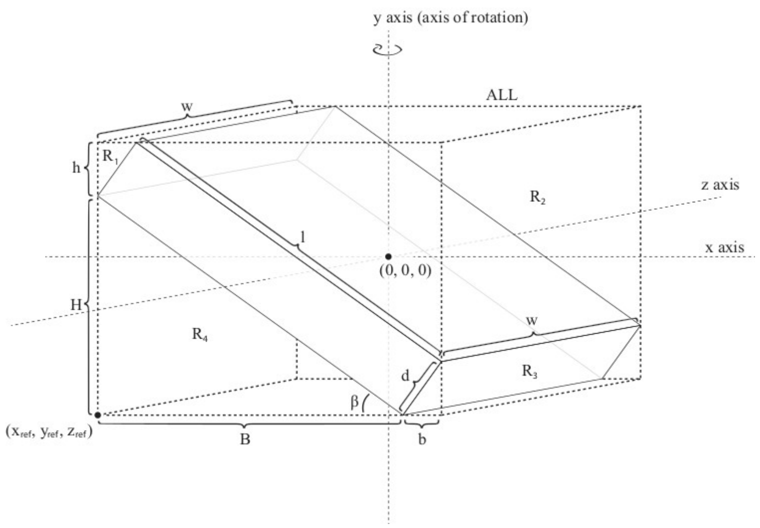
$$Cons_{\theta}^{sl} = \sum_{\mu=1}^{3} \left(\alpha_{\mu} I_{S} - T^{w}_{S_{(\theta,\mu)}} \right) \theta_{\mu}$$

- The consumption for θ is calculated as the **sum of the consumption of three motion types**

- Assumption of trapezoid motion: $\theta_1 = \theta_3 = \frac{\theta_2}{2} = \frac{\theta}{4}$

$$\alpha_1 = -\alpha_3 = \frac{9\theta}{2\delta^2}$$

$$\alpha_2 = 0$$



$$I_S = \frac{m}{12} (l^2 + d^2)$$

$$I_A = \frac{m}{12} (l^2 \cos^2(\beta) + d^2 \sin^2(\beta) + w^2)$$

$$T_X^w = \frac{1}{2} \rho w l^2 V^2 c_X, \textit{ where } X \in \{A, S\}$$

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A Dynamic Programming Approach

Optimal solar tracking

- MDP is very large to solve optimally

  Typically $|I| \cdot |S| \cdot |A| > 4$ ***Bn*** (without even considering $\boldsymbol{w_s}$)

- Approximation methods:
  - **Solar Tracking Policy Iteration** (STPI)
  - **Myopic**

- Next-Day-Optimal Fixed-Orientation

Approximation Methods

Solar Tracking Policy Iteration (STPI)

- **Alternatively optimizes over MDP action sub-spaces**
  - Expected to **converge to a fixed point**
  - **First time this technique is applied to MDPs**
- The **initial policy** we use is a **myopic** one which **maximizes power output alone**
- **High near-optimality guaranties**
  - The tracking consumption is less than 1% of the production
  - Lowering consumption leads to lower production

Algorithm 1 "Alternating" Policy Iteration for ST

procedure STPI(π)
  Initialize π_λ and π_κ based on π
  while π_λ and π_κ are not stable **do**
    $\pi_\lambda \leftarrow \textsc{SlopePI}(\pi_\lambda, \pi_\kappa)$
    $\pi_\kappa \leftarrow \textsc{AzimuthPI}(\pi_\kappa, \pi_\lambda)$
  Derive π' by combining π_κ and π_λ
  return π'

Algorithm 2 Slope Policy Iteration

procedure SLOPEPI(π_λ, π_κ)
  while π_λ is not stable **do**
    for all $\tau \in I$ in descending order **do**
      for all $s \in S$ that can emerge based on π_κ at τ **do**
        $a \leftarrow \langle \kappa_a = \pi_\kappa(s,\tau), \lambda_a = \pi_\lambda(s,\tau)\rangle$
        $V_\tau(s) \leftarrow \sum_{s'} P(s,a,s')\left(R_a(s,s') + V_{\tau+1}(s')\right)$
    for all $\tau \in I$ (in any order) **do**
      for all $s \in S$ that can emerge based on π_κ at τ **do**
        $\pi_\lambda(s,\tau) \leftarrow \operatorname{argmax}_\lambda \sum_{s'} P(s,a,s')(R_a(s,s')+$
          $V_{\tau+1}(s'))$, where $a = \langle \kappa_a = \pi_\kappa(s,\tau), \lambda_a = \lambda\rangle$
  return π_λ

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Approximation Methods

Myopic method

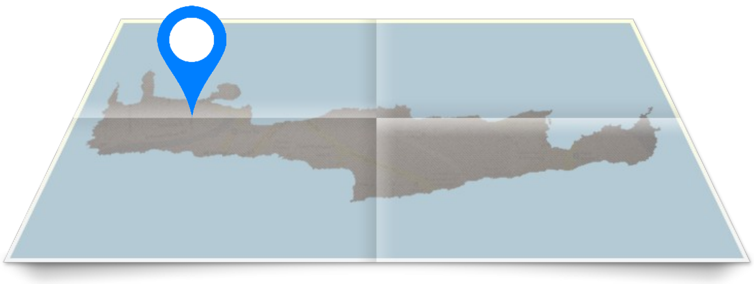
- **Maximizes power output <u>alone</u>** (disregarding any repositioning costs) $R_a(s,s')=Prod(s,s')$

- Recall that $G_T = G_B + G_D + G_R$ $\longrightarrow$ $\begin{aligned} G_B &= G_B^{max}\cos\theta_s \\ G_D &= G_D^{max}(1+\cos\beta)/2 \\ G_R &= G_R^{max}(1-\cos\beta) \end{aligned}$ hence:

  - For **AADAT** fixes the azimuth angle to follow the sun and optimizes the slope angle
  - For **VSAT** follows the sun over the azimuth and defines the best next-day fixed slope angle

Simulation Experiments

- Simulated a typical PVS in Chania, Crete



- Compared our methods against additional **baseline methods**:
  - **Chronological AADAT**
  - **Chronological VSAT**
  - A **yearly optimal fixed-orientation** system

Simulation Experiments

- Archival weather data (from wunderground) for four different days at our location of interest:
  - 20/03/2011 equinox **Day 1**
  - 22/09/2012 equinox **Day 2**
  - 21/06/2012 solstice **Day 3**
  - 21/12/2008 solstice **Day 4**

- Four additional **fictional dates** where**:** Wind Speed $\leftarrow$ 60 km/h

- Deterministic weather predictions
  - Weather forecast accuracy does not affect our methods' efficiency
  - Myopic becomes equivalent to sensor-based ST

The Results

Dataset	Day	Fixed-Orientation Year-Opt	Fixed-Orientation Next-Day-Opt	Single Axis ST (VSAT) Chronological	Single Axis ST (VSAT) Myopic	Single Axis ST (VSAT) STPI	Dual Axis ST (AADAT) Chronological	Dual Axis ST (AADAT) Myopic	Dual Axis ST (AADAT) STPI
Real	1	31.520 (-)	**32.448** (-)	32.533 (.027)	32.791 (.019)	**32.794** (.015)	32.021 (.061)	33.033 (.078)	**33.070** (.037)
	2	49.736 (-)	**50.275** (-)	52.036 (.029)	52.042 (.028)	**52.046** (.023)	51.624 (.063)	52.326 (.087)	**52.360** (.049)
	3	67.301 (-)	**68.921** (-)	71.037 (.039)	72.977 (.057)	**72.985** (.048)	73.434 (.091)	74.003 (.106)	**74.027** (.080)
	4	11.736 (-)	**11.748** (-)	11.623 (.019)	11.738 (.031)	**11.754** (.010)	11.465 (.037)	11.788 (.059)	**11.822** (.021)
Fictional	1	31.520 (-)	**32.448** (-)	32.530 (.030)	32.784 (.026)	**32.790** (.019)	31.899 (.183)	32.730 (.381)	**32.972** (.121)
	2	49.736 (-)	**50.275** (-)	52.034 (.031)	52.040 (.030)	**52.045** (.023)	51.515 (.172)	52.034 (.379)	**52.247** (.156)
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	4	11.736 (-)	**11.748** (-)	11.615 (.026)	11.729 (.041)	**11.751** (.010)	11.411 (.090)	11.567 (.280)	**11.747** (.032)

All energy values are in kWh, and correspond to PVS net energy gain (tracking consumption in parenthesis)

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- Chronological ST does not fully exploit the additional system abilities

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- Chronological ST does not fully exploit the additional system abilities
- Our methods clearly outperform the baseline ones:
  - Next-day optimal fixed-orientation significantly outperforms the yearly optimal one

The Results

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	2	49.736 (-)	**50.275** (-)	52.034 (.031)	52.040 (.030)	**52.045** (.023)	51.515 (.172)	52.034 (.379)	**52.247** (.156)
	3	67.301 (-)	**68.921** (-)	71.018 (.059)	72.961 (.074)	**72.977** (.055)	73.264 (.261)	73.706 (.404)	**73.862** (.237)
	4	11.736 (-)	**11.748** (-)	11.615 (.026)	11.729 (.041)	**11.751** (.010)	11.411 (.090)	11.567 (.280)	**11.747** (.032)

All energy values are in kWh, and correspond to PVS net energy gain (tracking consumption in parenthesis)

- Chronological ST does not fully exploit the additional system abilities
- Our methods clearly outperform the baseline ones:
  - Next-day optimal fixed-orientation significantly outperforms the yearly optimal one
  - Myopic gives a significant advantage over chronological tracking

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The Results

Dataset	Day	Fixed-Orientation Year-Opt	Fixed-Orientation Next-Day-Opt	Single Axis ST (VSAT) Chronological	Single Axis ST (VSAT) Myopic	Single Axis ST (VSAT) STPI	Dual Axis ST (AADAT) Chronological	Dual Axis ST (AADAT) Myopic	Dual Axis ST (AADAT) STPI
Real	1	31.520 (-)	**32.448** (-)	32.533 (.027)	32.791 (.019)	**32.794** (.015)	32.021 (.061)	33.033 (.078)	**33.070** (.037)
	2	49.736 (-)	**50.275** (-)	52.036 (.029)	52.042 (.028)	**52.046** (.023)	51.624 (.063)	52.326 (.087)	**52.360** (.049)
	3	67.301 (-)	**68.921** (-)	71.037 (.039)	72.977 (.057)	**72.985** (.048)	73.434 (.091)	74.003 (.106)	**74.027** (.080)
	4	11.736 (-)	**11.748** (-)	11.623 (.019)	11.738 (.031)	**11.754** (.010)	11.465 (.037)	11.788 (.059)	**11.822** (.021)
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All energy values are in kWh, and correspond to PVS net energy gain (tracking consumption in parenthesis)

- Chronological ST does not fully exploit the additional system abilities
- Our methods clearly outperform the baseline ones:
  - Next-day optimal fixed-orientation significantly outperforms the yearly optimal one
  - Myopic gives a significant advantage over chronological tracking
  - STPI does consistently better than Myopic/Sensor-based
    Even though not by a wide margin

The Results

Dataset	Day	Fixed-Orientation Year-Opt	Fixed-Orientation Next-Day-Opt	Single Axis ST (VSAT) Chronological	Single Axis ST (VSAT) Myopic	Single Axis ST (VSAT) STPI	Dual Axis ST (AADAT) Chronological	Dual Axis ST (AADAT) Myopic	Dual Axis ST (AADAT) STPI
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All energy values are in kWh, and correspond to PVS net energy gain (tracking consumption in parenthesis)

- Such small improvements are not surprising
  - The tracking consumption is much lower than the energy produced (less than 1%)
  - Lowering consumption leads to lower production (up to ~90% reduction in consumption)
- For a 2MW PV park → over €1500 more by using STPI, compared to Myopic (and over €10000 compared to chronological AADAT) annually
- Smaller PVSs → higher consumption over production ratio, and higher expected improvement from using STPI

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Conclusions and Future Work

- We formulated ST as a dynamic programming problem
- We approximate the optimal solution (STPI, Myopic) utilizing available weather forecasts
- We propose a generic and parameterizable tracker power consumption model
- We demonstrated our methods' efficiency against commonly employed ST techniques
- Our methods come with optimality or near-optimality guarantees

Our methods can serve as the basis for web-based tools for efficient predictive ST

- Future work:
  - Incorporate additional details in our consumption model
  - Modify our methods to account for additional tracking systems (e.g, pole trackers)
  - Consider weather forecast updates throughout the operation day, in real-time

Thank you! Any questions?