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SUPPLEMENTARY INFORMATION

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# Quantifying the impacts of climate change and extreme climate events on energy systems

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# Supplementary Information

## Quantifying the impacts of climate change and extreme climate events on energy systems

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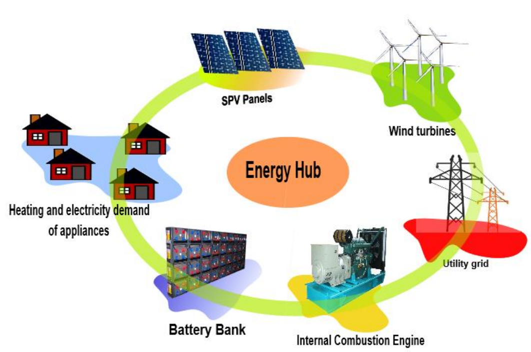
### Supplementary note 1. Outline of the energy system

Energy hub concept was introduced by Geidl et-al. *[1,2]* to incorporate energy technologies with different characteristics in order to cater the demand for multi-energy services (Supplementary Figure 1). Energy hub concept has already received the attention of a wider group of researchers working on distributed generation. Furthermore, it has shown the potential to incorporate more renewable energy technologies *[3]*. The energy hub considered in this study operated in connection with the local electricity grid. The energy hub injects electricity to the grid when there is an excess generation (and also the cost of selling is competitive) and purchases electricity from the grid to cater the mismatch between demand and generation. Grid curtailments have been introduced both for selling and purchasing electricity to and from the grid to guarantee the stability of the grid. The energy hub considered in this study consists of wind turbines and Solar PV (SPV) panels which are non-dispatchable energy technologies. An Internal Combustion Engine (ICG) is used as the dispatchable generator. A battery bank is used the energy storage assisting ICG and grid to absorb the fluctuations in both demand and generation. It is assumed that the heating demand is catered using heat pumps.




**Supplementary Figure 1 Outline of the energy system**

## Supplementary note 2. Energy flow model

Energy flow through system components such as solar PV (SPV) panels, wind turbines etc. is considered under the energy flow model. Based on the hourly solar irradiation, solar power generation ( $P_{t,s}^{SPV}$ ) is computed using Eq.1

$$P_{t,s}^{SPV} = G_{t,s}^{\beta}\, \eta_{t,s}^{SPV}\, A^{SPV} N^{SPV}\, \eta_{Sys}^{SPV}, \quad \forall t \in T, \forall s \in \Omega \tag{1}$$

In this equation, t denotes the time step ( $\forall t \in T$ ) and *s* denotes the scenario that belongs to the set of *Ω,* which presents all the scenarios (union of *Ψ* and *π* sets of scenarios representing stochastic and robust scenarios respectively). In Eq. 1, $G_{t,s}^{\beta}$ , $A^{SPV}$ , $N^{SPV}$ $(N^{SPV} \in \mathrm{N})$ denote the global solar irradiation on a tilted SPV panel, surface area of the SPV panel and number of SPV panels in the system respectively. $\eta_{Sys}^{SPV}$ takes into account the minor losses in the SPV system due to dust accumulation and the power losses in the inverters. $\eta_{t,s}^{SPV}$ denotes the efficiency of the SPV panel which is computed using Eq. 2.

$$\eta_{t,s}^{SPV} = p^{SPV}\left[\mathrm{q}^{\mathrm{SPV}}\left(\frac{G_{t,s}^{\beta}}{G_{0}^{\beta}}\right)+\left(\frac{G_{t,s}^{\beta}}{G_{0}^{\beta}}\right)^{m^{SPV}}\right]\left[1+r^{SPV}\left(\frac{\theta_{t,s}^{SPV}}{\theta_{0}^{SPV}}\right)+s^{SPV}\left(\frac{AM}{AM_0}\right)+\left(\frac{AM}{AM_0}\right)^{u^{SPV}}\right], \quad \forall t \in T, \forall s \in \Omega \tag{2}$$

In Eq. 2, Standard values for $G_0^{\beta}$ , $\theta_0^{SPV}$ , $AM_0$ are taken respectively as $G_0^{\beta}$ = 1000 $Wm^{-2}$, $\theta_0^{SPV}$ = 25°C and $AM_0$ = 1.5. Parameter values of $p^{SPV}$ , $\mathrm{q}^{\mathrm{SPV}}$ , $r^{SPV}$ , $s^{SPV}$ , $m^{SPV}$ , $u^{SPV}$ for different SPV technologies, such as mono-crystalline, polycrystalline and amorphous silicon cells, are taken from Ref. [4]. AM denotes the air mass value and $\theta_{t,s}^{SPV}$ is the cell temperature. Similarly, power generation from the wind turbines is computed using Eq. 3.

$$P_{t,s}^{W} = \tilde{P}_{t,s}^{W}(\mathrm{v}_{\mathrm{t},s}^{Hub})\ \mathrm{N}^{\mathrm{w}}\ \eta^{\text{W-losses}}, \forall t \in T, \forall s \in \Omega$$

$$\tilde{P}_w(t) = \begin{cases} \tilde{P}_w = 0, & v_{hub}(t) < v_{ci} \\ \tilde{P}_w = a_1 v_{hub}^3 + b_1 v_{hub}^2 + c_1 v_{hub} + d_1, & v_{ci} < v_{hub}(t) < v_1 \\ \tilde{P}_w = a_2 v_{hub}^3 + b_2 v_{hub}^2 + c_2 v_{hub} + d_2, & v_1 < v_{hub}(t) < v_2 \\ \dots\dots\dots\dots\dots & \\ \dots\dots\dots\dots\dots & \\ \tilde{P}_w = a_{n_x} v_{hub}^3 + b_{n_x} v_{hub}^2 + c_{n_x} v_{hub} + d_{n_x}, & v_{n_x-1} < v_{hub}(t) < v_{n_x} \\ \tilde{P}_w = P_r, & v_r < v_{hub}(t) < v_{co} \\ \tilde{P}_w = 0, & v_{co} < v_{hub}(t) \end{cases} \tag{3}$$

In Eq. 3, $\tilde{p}_{t,s}^{W}$ denotes the power generated by a single wind turbine. According to Thapar et-al [5], wind turbine models using presumed shapes (based actual shape of the performance curve of the wind turbines) are more accurate. Hence, the cubic-spline interpolation method is used in this study to present the power curve of wind turbine (based on actual wind turbine found in market). In Eq. 3, $N^{W}$ $(N^{W} \in \mathrm{N})$, $\mathrm{v}_{\mathrm{t},s}^{Hub}$ denote the number of wind turbines and wind speed at the wind turbine hub height. Similar to Eq. 1, $\eta^{\text{W-losses}}$ presents the minor losses that take place in the energy conversion. Power generation in the internal combustion generator and the energy flow through the battery bank are computed in a similar manner. Detailed energy flow models used for the simulation can be found in Ref. [6–9] (in deterministic format).

## Supplementary note 3. Dispatch strategy

The dispatch strategy helps to accommodate the fluctuations in demand and generation while determining the interactions with the grid, energy storage and internal combustion generator. A bi-level dispatch strategy introduced in Ref. [3] is used in this study. The primary level of the dispatch strategy determines the operating load factor of the internal combustion generator based on renewable energy potential, energy demand, cost of energy in the grid and state of charge level of the battery bank. The fuzzy-automata theory is used at the primary level. The secondary level determines the interactions with the storage and the grid. The finite automata theory is used to assist the secondary level of the dispatch strategy. Both fuzzy rules and state transfer points of the dispatch strategy are considered as decision space variables. Based on the energy flow simulation, interactions with the grid, fuel consumption and wearing of internal combustion generator, charge/discharge cycles of the battery bank etc. are computed. These are used in both robust and stochastic blocks to formulate objective function values and constraints. A detailed description of the dispatch strategy is presented in Ref. [3].

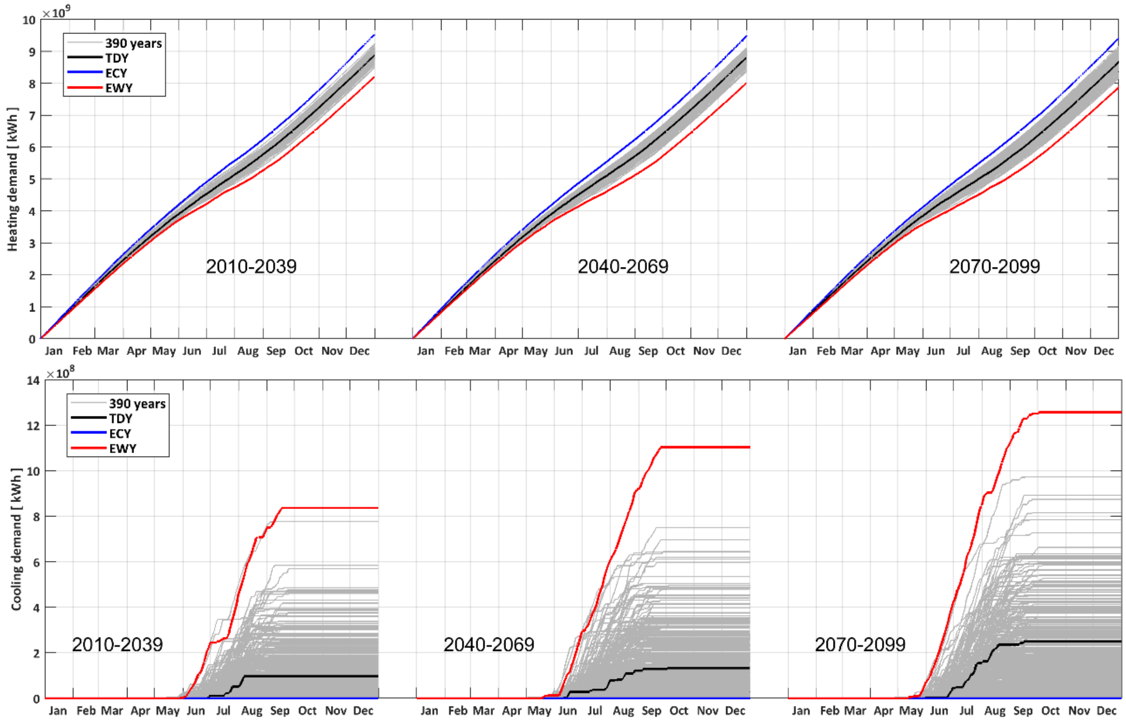
## Supplementary note 4. Time series demand and renewable energy generation

RCM data were used to synthesize two groups of representative weather data sets for a 30-year period, each group including three one-year weather data sets: one typical downscaled year (TDY), one extreme cold year (ECY) and one extreme warm year (EWY) [10]. The difference between the two groups is the adopted time frame, resulting in picking the representative month or hour. Synthesizing TDY, ECY and EWY on the monthly basis is explained in detail in [10]. In short, the method is based on Finkelstein–Schafer (FS) statistics: picking the single month with the closest cumulative distribution temperature to whole months (13×30=390 months in this case). This will give TDY and for ECY and EWY, the months with the largest absolute differences are picked. Supplementary Figure 2(a) shows the application of TDY, ECY and EWY in estimating the typical and extreme heating and cooling demand of the considered urban area in Malmö. TDY nicely represents the average conditions while ECY and EWY mark the (pessimistic) boundaries (for details see [10]).

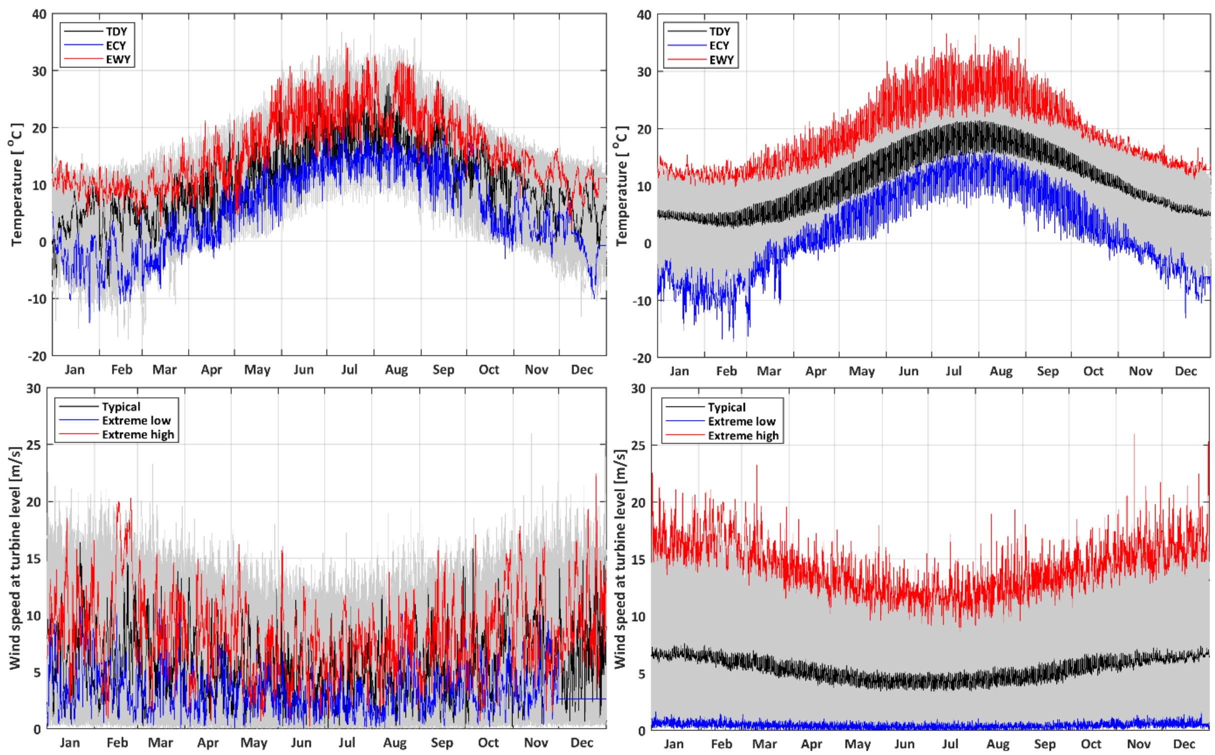
The method is developed further so as to track all possible extremes at each time step for any climate variable. To do so, the typical and extreme values of a climate variable were picked according to the hourly distribution at each time step (hour) considering all the years and climate scenarios (13×30=390 data points at each hour). This results in three time series (with the length of 8760 hours), each containing the most typical, the lowest and the highest values at each time step. These new data sets are generated only for calculation purposes and they cannot be considered as weather data since they do not reflect the natural variations of the climate system (unlike the monthly-based TDY, ECY and EWY which reflect natural variations). This is visible in Supplementary Figure A2(b); figures on the left compare all the 390 probable future conditions (light grey lines) with the monthly-based typical and extreme data sets. Similar comparison is performed on the right side for the hourly-based representative data sets. Although the annual profiles for the hourly-based do not represent natural variations of climate, they clearly mark the (pessimistic) boundaries. It is important to remember that each hourly value is a possible future condition (according to climate models) and can challenge the energy and urban infrastructures in the future.

In this approach, a number of scenarios are synthesized to represent future weather conditions, each containing certain number of data sets which are arranged on the basis of the expected values of any (desired) climate variable. Like the previous approach, all the 390 years of weather data (13 scenarios, each for a 30-year period) are accommodated in one year. By generating the cumulative distribution of a climate variable at each hour and calculating its percentiles, the value of the climate parameter can be calculated for different probabilities. For example, if wind speed varies between 0 to 20 m/s during one year (see Supplementary Figure 3), by dividing the range of values into 9 sequences (see the legend in Supplementary Figure 3), the first 5% (‘F9-1’) represent the lowest wind speed values during the whole year, while the last 5% (‘P9-9’) represent the highest. In other words, ‘F9-1’ is a pseudo-sequential time series with one value at each time step that represents the percentiles between 0 and 5, while ‘F9-9’ represents percentiles between 95 to 100. Four scenarios have been generated in this work by synthesizing pseudo-sequential time series for three (20-60-20%), five (10-20-40-20-10%), seven (10-15-15-20-15-15-10%) and nine (5-5-15-15-20-15-15-5-5%) sequences, which are called ‘expected scenarios’ hereafter. It is noteworthy to remember that the time series of the expected scenarios do not represent the natural variations of the climate system.

The described method can be applied to any variable with many possible values at each time step, as is adopted in this work for creating the expected scenarios for renewable generation potentials and energy demand. Since detailed information is not available for grid curtailments and grid prices, only three sequences (20-60-20%) are considered, based on Ref. [3] and [11].

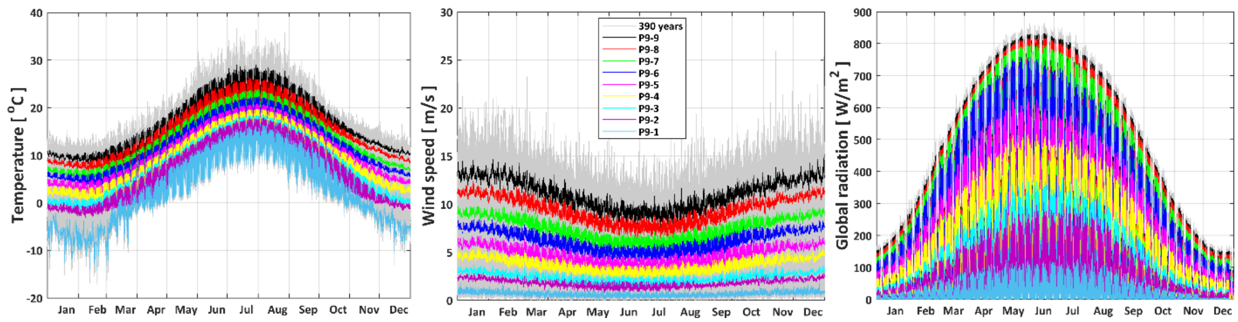



**Supplementary Figure 2(a).**




**Supplementary Figure 2(b).**

**Supplementary Figure 2 (a): Cumulative distribution of (top) heating and (bottom) cooling demand for an urban area in Malmö considering 13 climate scenarios and the synthesized typical (TDY), extreme cold (ECY) and extreme warm (EWY) weather data sets. (b) Hourly distribution of (top) outdoor temperature and (bottom) wind speed at the wind turbine level (60 m) for 13 climate scenarios during 2070-2099 (390 profiles – light grey lines) and the typical and extreme conditions when they are picked based on the (left side) monthly distributions according to** [10] **and (right side) hourly distributions of temperature.**




**Supplementary Figure 3. Hourly distribution of (left) outdoor air temperature, (middle) wind speed at the wind turbine level, and (right) global radiation for 13 climate scenarios during 2070-2099 (390 profiles – light grey lines) and the hourly time series of expected values considering nine probability values (P9-1 – P9-9).**

## Supplementary note 5. Present state of the art methods for energy system design

When assessing the impacts of climate change, climate projection uncertainties and a large number of data sets represent two major challenges. Several models with different scenarios simulate possible future climate conditions, but no single simulation can be considered the most probable. Moreover, periods of 20 to 30 years should be considered when performing the impact assessment of climate change [12]. Thus, a valid impact assessment should take into account several long-term future climate scenarios. This will increas the size of data sets and the complexity of further analyses, making it difficult to convert climate relevant data into energy system relevant data.[13]

It is vital to handle uncertainties in the energy system optimization process to guarantee the robust operation and resourcefulness of an energy system facing climate change and extreme conditions. A number of studies have focused on design optimization of energy systems under uncertainty, and these have been reviewed.[14,15] Sharifi and Yamagata[16] critically discuss the importance of considering climate resilience during the energy system design process, explaining the need to extend the available approaches to account for uncertainties. Recent literature on energy system optimization that considers the uncertainty of demand, renewable energy generation, grid condition, etc. can be classified into two main groups, based on the number of days considered for time series simulation: selected days and hours (SSD) (e.g.,[17,18]); limiting the number of time steps makes it feasible to increase the number of scenarios considered for stochastic optimization, and entire annual time series simulations (ETS); considering 8,760 time steps for each scenario when conducting stochastic optimization (e.g.,[19,20]).
The SSD method facilitates consideration of the unit commitment problem in detail, enabling the design of complex energy systems. However, reducing the length of the time series can notably influence the final design, especially when considering non-dispatchable energy technologies. For example, according to [21,22] using three to five days to represent 365 days may result in a notable deviation from actual conditions. More important, such an approach cannot be used directly to represent extreme climate events that may take place for periods longer than one week. Such extreme events can occur in different seasons, and the probability can also be higher for future climatic conditions. Therefore, it is challenging to extend SSD to design resilient distributed energy systems.

Several studies have considered the ETS (8,760 time steps) in stochastic optimization.[17,18] Such a detailed representation enables a model to be more accurate and closer to reality, especially in the context of representing energy systems with a larger capacity of non-dispatchable energy technologies. However, a relatively simple dispatch strategy needs to be used in the design of the optimization process (one of the main limitations of using this method) when incorporating ETS. In addition, non-linear optimization methods should be accommodated, although this will significantly increase computation time. As a result, the number of scenarios considered in the stochastic optimization process is notably reduced. For example, Narayan and Ponnambalam[18] limited the stochastic optimization scenarios to 200. Limiting the number of scenarios considered for stochastic optimization (especially when using scenario reduction methods that follow a Monte Carlo simulation) often eliminates extreme climate conditions. Therefore, a notable improvement is essential when extending the ETS based on the entire time series simulation to accommodate both climate uncertainty and extreme climate events. A more detailed justification about the proposed workflow is found in Supplementary Table 1

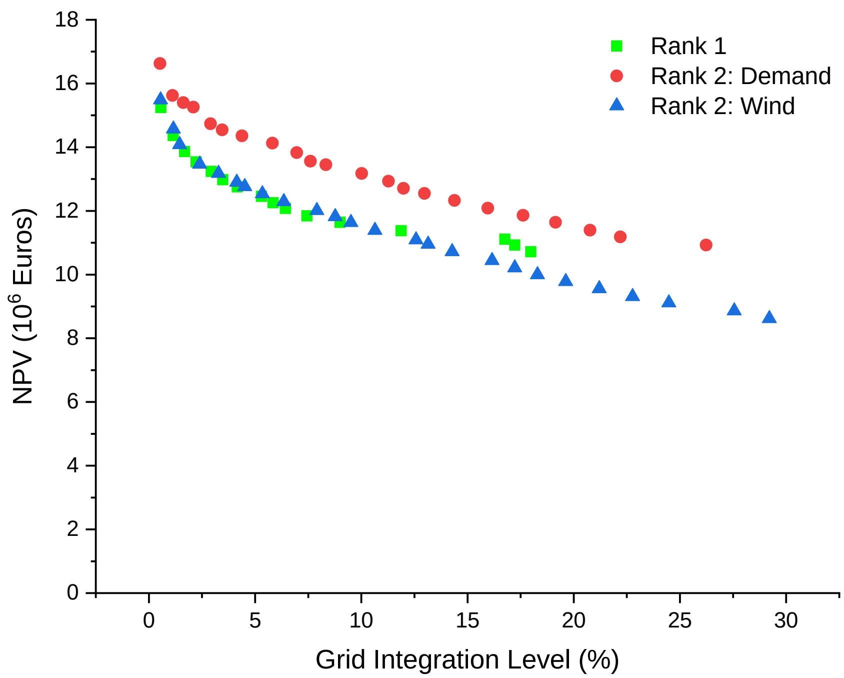
## Supplementary note 6. Scenarios with alternative rankings

The scenario tree used in this study considers both climate based as well as non-climate based (which indirectly influence the climate relevant factors). The uncertainties of climate-based factors are obtained by assuming them to be independently driven factors since it is challenging to develop a joint distribution considering the influence of each on the energy system. The results obtained by using this approach is presented in the main body (named as Rank 1). in this section, we consider one factor at a time when developing scenarios instead of considering them as three independent driven factors. Although such a consideration does not provide the multi-dimensional impacts due to climate change, it provides a comprehensive figure about each sector separately. Two Pareto fronts are taken with alternative scenarios considering one factor at a time i.e. energy demand and wind energy driven as shown in Supplementary Figure 4.

When considering the energy demand (Rank 2: Demand), wind driven (Rank 2: Wind) scenarios lead to a higher cost. Climate change notably reduces the heating demand consequently; misrepresentation impact of climate change on energy demand will lead to show a higher cost, which can be around 14.5%. Energy demand driven scenario solely use temperature when developing the scenarios. Pareto front for the energy demand scenario coincides with Rank 1. This implies that, such a detailed representation of uncertainties (considering them as three independent factors) are not required in this specific case for a major part of the Pareto front. However, a notable difference is observed for scenarios having higher grid integration level. This is mainly due to the extreme conditions, which can be understood when comparing the SO, and SRO Pareto fronts in Fig. 5. Although the scenarios developed concerning demand performs reasonably well when concerning the high probable low impact scenarios (concerning this specific location), it is not effective when it comes to low probable high impact scenarios. Therefore, it would be interesting to look over scenario reduction methods (at least concerning high probable low impact scenarios) which can immensely reduce the computation burden of the problem.

Supplementary Table 1: Workflow proposed in this study and the detailed justification

| Element in the Work Flow | Description |
|---|---|
| Climate data | Several future climate data sets were synthesized as inputs to the urban energy simulation models. The pool of weather data were created by using RCA4 regional climate model (the 4th generation of the Rossby Centre climate model, which was used for downscaling in CORDEX using CMIP5 GCMs as boundary conditions [23]), considering 13 climate scenarios with different GCMs and RCPs (RCP2.6, 4.5 and 8.5). We decided to use only CMIP5 scenarios, since the implementation of CMIP6 has been delayed and only a few modeling centers in the world have been able to deliver the new scenarios as planned. The preparation and synthesis of RCA4 outputs to generate weather files suitable for energy simulations is a lengthy procedure which is thoroughly discussed in previous works of the authors (e.g., [24] [25] [26]). |
| Building simulation model, solar irradiation model, and wind speed model | Taking the input from the climate model, a building simulation model was used to compute the energy demand of the building stock. In a similar manner, solar irradiation [27] on a tilted surface and wind speed at the wind turbine hub level [28] were computed.<br>The building simulation model used in this study was validated and already presented in number of publications (e.g., [26] [29] [30]). Similarly, we used models for solar irradiation and wind speed computation, which are well established in the literature. |
| The concept of high probability, low impact and low probability, high impact scenarios<br><br><br><br><br>Methodology used to derive time series for HPLI and LPHI scenarios concerning energy demand and renewable energy potentials | <u>The concept of high probability, low impact and low probability, high impact scenarios</u><br>Using high probability, low impact as well as low probability, high impact scenarios has been established for more than one decade. It is a well-known concept in project management and amply used with engineering projects [31]. There is a large pool of literature that has looked into this from the uncertainty perspective, such as [32]. Considering climate, most of the literature is focused on low probability / high impact scenarios, and often they do not discuss the long-term performance of the designed infrastructure [33]. Concerning the energy system, the concept was introduced by Molyneaux et al. [34], while they did not formulate it as a mathematical problem.<br><u>Methodology used to derive time series for HPLI and LPHI scenarios concerning energy demand and renewable energy potentials</u><br>Nik [24] proposed a methodology based on the ranking of cumulative hourly temperature (outdoor temperature or $T_{dry\ bulb}$ on the hourly resolution for each month). In the current work, we have extended the methods presented in Nik (2016) [24] to have a more detailed representation of extreme conditions and address the critical conditions that may challenge the resilience of urban energy systems. Therefore, in this work, we generated three groups of weather files, each based on one climate variable that is the most critical for the purpose (outdoor temperature for energy demand, solar irradiation for solar PV generation, and wind speed for wind turbine generation). More important, it adheres to the basic principles used to model uncertainties in energy systems, as in Jordehi et al. [35]. |
| Energy system model | The energy flow model used in this study has been amply used by the authors and previously validated concerning the deterministic scenario [3,36–40]. |
| Stochastic-Robust optimization | A hybrid stochastic robust optimization model has been used to consider HPLI and LPHI when conducting the dispatch optimization of energy systems considering the uncertainties of grid conditions by [41]. We used the same approach to consider HPLI and LPHI scenarios in energy system optimization. |




**Supplementary Figure 4: Comparison of Pareto fronts obtained using SRO method for two alternative sets of scenarios**

## Supplementary note 7. Reference algorithm

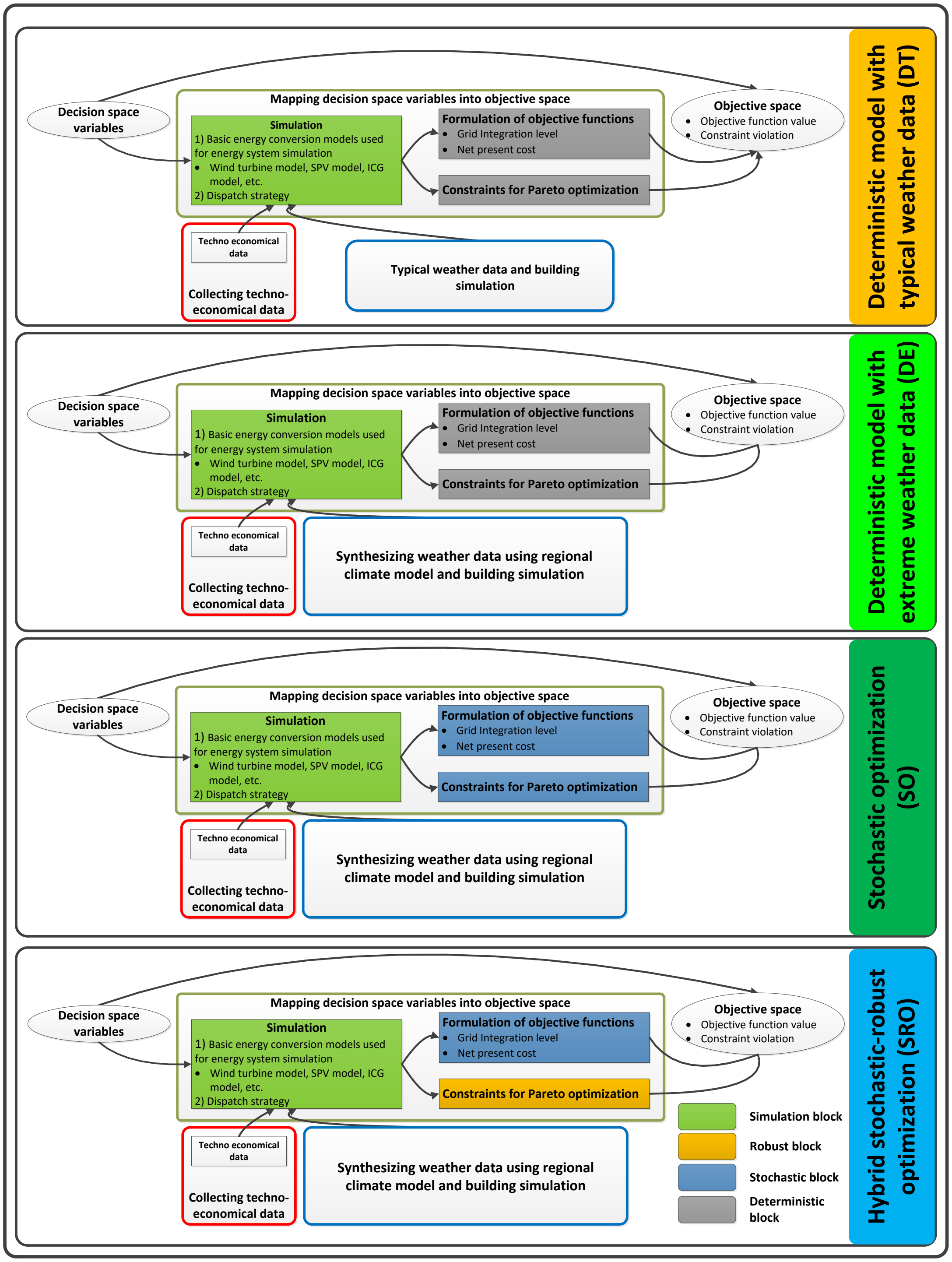
Several reference algorithms are used to compare the performance of the novel algorithm introduced in this study. Outline of these algorithms are presented in Supplementary Figure 5.

### Deterministic model with typical weather data (DT)

The deterministic model is generally used to design distributed energy systems based on typical weather data as is the case in this work. Several typical weather data sets are available, of which TMY is one of the well-known formats, widely used for energy simulations. In this work, instead of using TMY or similar available data sets, typical weather data have been synthesized using outputs of the RCA4 regional climate model, which is called Typical Downscaled Year (TDY). TDY is used to simulate the energy demand of the buildings and the energy system. Both objective functions and constraints are derived based on the deterministic model.

### Deterministic model with extreme weather data (DE)

The main weakness in the deterministic model is not considering the extreme climate conditions. Therefore, it is difficult to guarantee the robustness of the energy system under extreme events. The DE algorithm (as shown in Supplementary Figure 5 **Error! Reference source not found.**) is used to design the energy system replacing the typical weather data by extreme climate conditions (extreme high and low – check Section 3).




**Supplementary Figure 5: Comparison of different algorithms used as reference algorithms to compare the performance of the proposed SRO. Respectively from top to bottom, outline of DT, DE, SO and SRO are presented. Climate scenarios obtained from regional climate model are introduced DE onwards (when moving from top to bottom). Deterministic formulation is replaced entirely by using the stochastic models in SO. The robust programing method is used in SRO to evaluate the constraints.**

### Stochastic optimization (SO)

As discussed before, stochastic programing is a more realistic way to represent uncertainties, especially when compared to deterministic models. Stochastic programing is used to compute both objective functions and constraints for the optimization algorithm in this algorithm (Supplementary Figure 5).

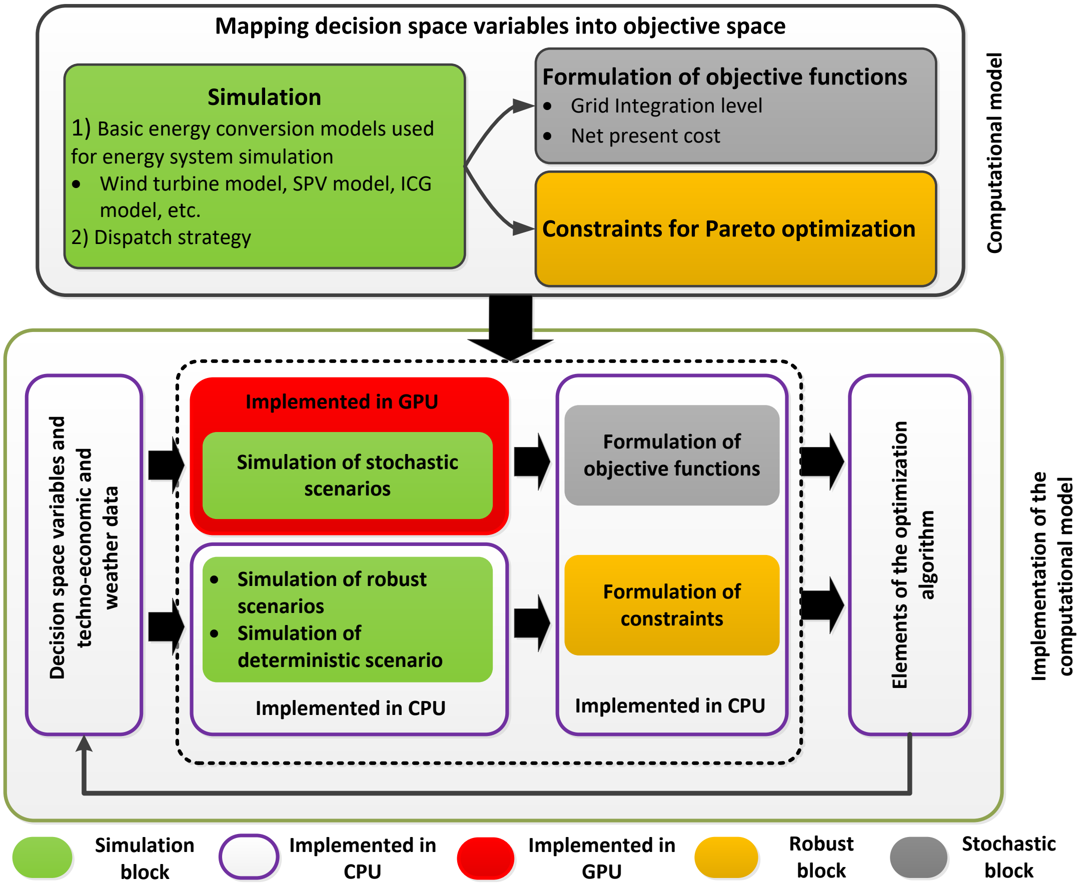
### Hybrid stochastic-robust optimization (SRO)

SRO is the novel method introduced in this study and detailed in Methodology section. Compared to SO, robust programing is used in SRO to consider the extreme events.

## Supplementary note 8. Implementation of the computational algorithm

Simulation based optimization is a time consuming activity which gets more challenging by accommodating large number of scenarios that consider lengthy simulations. Hence, efficient implementation of the computational program plays a vital role. In order to accomplish this objective, Graphical Processor Unit (GPU) computing is introduced in this study to conduct time series simulation. GPU computing facilitates large scale parallelization of computational program. As a result, GPU computing has been already used in different fields such as image processing, machine learning, bio-informatics etc. However, GPU computing is not well known among the energy system designing community despite of its potential to speed up computational processes. When considering stochastic optimization, GPU computing makes it feasible to handle large number of scenarios within a reasonable computational time.

Formulation of the objective functions is explained using three blocks in main body in order to make it easy for the readers the understand (Figure 2 in the main body). The computational algorithm begins in a similar manner following the mathematical model (Supplementary Figure 6). The techno-economic and weather data are collected and provided to the computational algorithm. The Simulation block (considered as one part) which includes the set of computational models is divided into two parts and implemented in both CPU and GPU. Scenarios related to the stochastic programing part are implemented in the GPU which support large scale parallelization. Scenarios related to the robust part and deterministic part is implemented in Central Processing Unit (CPU). Subsequently, the objective function values and constraints are computed in the CPU aggregating the computation performed in both CPU and GPU. Based on the objective function values, the population and archive are updated following the dominance check using the CPU.



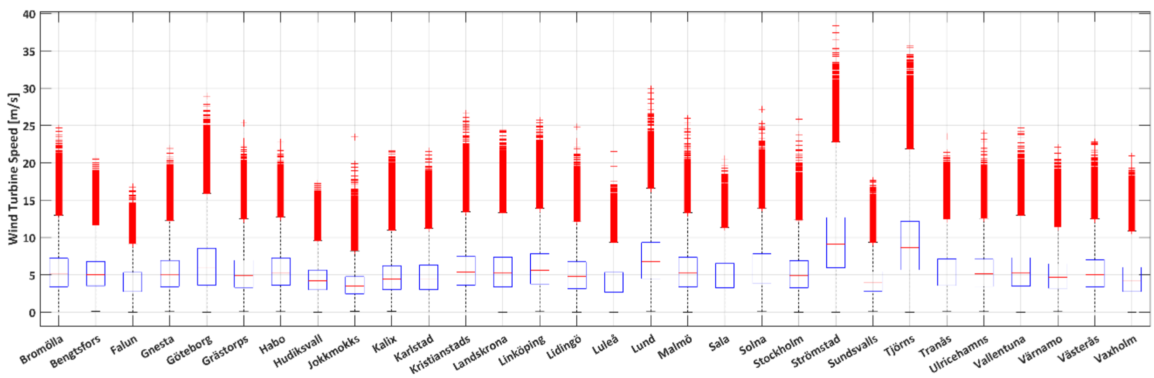

**Supplementary Figure 6. Implementation of the computational algorithm**

## Supplementary note 9. Overall Computational Platform

Section 6 solely presents the computation process within the energy system design process. However, energy system design process links with building simulation climate models etc. that demands for much larger computation time. Most of the tasks in energy system optimization and energy system optimization are sequential tasks that cannot be parallelized. For example, evaluation of objective function value should be performed sequentially (same applies to the building simulation). When we consider climate data as direct input to the model (neglecting the computation time), urban simulation takes 15 hours for one climate scenario and 95 years (2006-2100) (for the building stock in Stockholm (153 buildings)). The computation time varies with the number of buildings considered. The energy system optimization takes two days to conduct SRO optimization for a location. Altogether, it is an extensive computation task. For energy system optimization, it takes approximately two days for a stochastic-robust scenario to conduct the optimization (when using HP Z8 G4 Workstation with:Intel(R) Xeon(R) Gold 6244 CPU@360GHz (32 CPUs) with NVIDIA Quadro rTX 6000).

## Supplementary note 10 Wind speed variation

Supplementary Figure 7 presents the variation of wind speed in 30 cities.




**Supplementary Figure 7: Box plot representing the variation of wind speed**

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