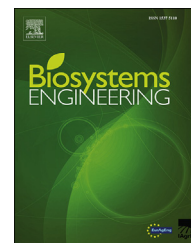


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Research Paper

Proactive energy management of solar greenhouses with risk assessment to enhance smart specialisation in China



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ARTICLE INFO

Article history:

Received 21 September 2016

Received in revised form

28 February 2017

Accepted 19 March 2017

Keywords:

Solar greenhouse

System identification

Smart energy

Risk management

For better time-allocation of stored energy, the solar greenhouse (SGH) is equipped with some storage devices designed economically for local weather: wall storage actively managed with energy-store/retrieve fans and Safety Energy (SE which is a solar collector and fully thermally isolated heat tank) designed for non-regular extreme weather. A proactive energy management process, addressing the optimal energy utilisation through dynamic cooperation of the wall and the SE, is presented in this paper. Based on probabilistic weather forecast and a SGH thermal model, found by system identification, the operation set-points are optimised proactively by minimising the plant probable thermal "cost" and weather-related risk in a scheduling period to take pre-emptory action against potential emergencies. The optimisation is formulated in a two-level control scheme. A master problem optimises the primary (wall-soil) storage operation against the expected weather, and a sub-problem operates the SE as a supplement to the limited wall storage in order to create a better indoor environment. The main task of the slave problem manager is to find the optimal SE operation under probable extreme weather to keep reserves to minimise any risk of severe crop loss. The overall optimisation is solved by a hybrid evolutionary algorithm based on a genetic algorithm. The tests show good potential for energy saving and crop cold stress minimisation, as well as great tolerance to forecast errors for most of the cases in Monte-Carlo simulation. The capacity of the proposed real-world system to implement the tested risk management scheme over web "recommendations" satisfies the need to close the loop of an effective Internet of Things (IoT) system, based on the MACQU (Management And Control for QUality) technological platform.

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<http://dx.doi.org/10.1016/j.biosystemseng.2017.03.007>

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Nomenclature	
$[\cdot]_+$	function $\max(\cdot, 0)$
$f_C(\cdot)$	a function of T_i & T_w calculating cost value
$f_R(\cdot)$	a function of T_i & T_t calculating risk value
$g(\cdot)$	evaluating value of the management, °C h
I_{rad}	solar radiation, $W m^{-2}$
$J(\cdot)$	objective function (composed by J_R & J_C)
$J_C(\cdot)$	cost function of set-points
$J_R(\cdot)$	risk function of set-points
L_{cl}	cold loss of crops
L_{hl}	heat loss of crops
L_{SE}	loss of SE to prevent overuse
L_{TL}	total loss of crops caused by freezing
N	planning period
P_1, P_2, P_3	parameters of the greenhouse model
S/R	energy-storage/retrieval
SE	safety energy
SGH	solar greenhouse
SGHSEW	SGH with both active wall and SE system
SGHW	SGH with active wall but no SE
T_{br}	best T_{ir} found by proactive management, °C
T_{bs}	best T_{is} found by proactive management, °C
T_{bSE}	best T_{iSE} found by proactive management, °C
T_{chigh}	high failure temperature point for crops, °C
T_{clow}	low failure temperature point for crops, °C
T_{cmax}	the maximum appropriate T_i for crops, °C
T_{cmin}	the minimum appropriate T_i for crops, °C
T_{cTL}	the freezing point causing total loss, °C
T_i	indoor air temperature, °C
T_{iExp}	T_i predicted by expected weather, °C
T_{iExt}	T_i predicted by extreme weather, °C
$T_{i,F}$	resultant T_i with fixed set-point, °C
$T_{i,N}$	resultant T_i in SGH without active wall storage and SE system, °C
$T_{i,P}$	resultant T_i of proactive management, °C
T_{ir}	set-point for wall energy retrieval, °C
T_{is}	set-point for wall energy storage, °C
T_{iSE}	set-point for SE management, °C
$T_{i,SEW}$	resultant T_i in SGHSEW, °C
$T_{i,W}$	resultant T_i in SGHW, °C
T_{iw}	set-points for wall energy management (including T_{is} & T_{ir}), °C
T_o	outdoor air temperature, °C
T_{soi}	soil temperature, °C
T_t	water temperature in SE tank, °C
T_{tExt}	T_t predicted by extreme weather, °C
T_{tLim}	limitation for SE utilisation, °C
T_w	wall temperature, °C
T_{wExp}	T_w predicted by expected weather, °C
$T_{w,F}$	resultant T_w with fixed set-point, °C
$T_{w,N}$	resultant T_w in SGH without active wall storage and SE system, °C
$T_{w,P}$	resultant T_w of proactive management, °C
$T_{w,SEW}$	resultant T_w in SGHSEW, °C
$T_{w,W}$	resultant T_w in SGHW, °C
u_c	control input for curtain
u_f	control input for the S/R fan
u_{SE}	control input for SE system
u_v	control input for ventilation windows
V_{wd}	wind speed, $m s^{-1}$
W_{cl}	weight for cold loss
W_{hl}	weight for heat loss
W_{SE}	weight for SE storage
W_{TL}	weight for total loss
W_{ws}	weight for wall storage
ω_{Exp}	expected weather condition (most probable)
ω_{Ext}	extreme weather condition (less probable)

1. Introduction

The Agricultural Modernisation priority of China's five-year program 2016–2020 is instrumental in fostering the political space for Smart Specialisation (European Union, 2012). The mission to support science-based innovation in the agri-food sector and the broader *knowledge bio-economy era* is what is expected to underpin competitiveness sustainability and prosperity in rural China, and other developing areas, as well as the globe of agricultural production.

Smart Specialisation represents the most comprehensive industrial policy experience being implemented in contemporary and developing countries and it is a promising effort to drive countries and regions out of the World crisis and guarantee opportunities for growth. This effort is calling, for the first time, for public authorities and stakeholders worldwide to craft their innovation policies according to a common set of principles to balance globalisation effects and respect nature and human rights.

High resolution energy management is important and necessary from a sustainability perspective for solar greenhouses (SGHs), or other modern low emission design structures, because of large energy flows and associated energy-footprints and high demand for agricultural productivity in quantity and quality. It is important to address the peak mismatch between solar energy supply and plant demand especially for the totally solar-energy dependent SGHs. Storage devices, as a promising solution to this problem (Alkilani, Sopian, Alghoul, Sohif, & Ruslan, 2011; Vadiie & Martin, 2012), can also reduce the fluctuations brought about by renewable energy sources and the uncertainty in predictions of both generation and demand (Arnold & Andersson, 2011).

A wealth of research effort is being focused today on optimal design and energy management of greenhouses coupled with various active or passive systems for energy saving/storage/heating, to maintain the inside microclimate satisfying crop needs for high productivity and energy sustainability (Alkilani et al., 2011; Attar, Naili, Khalifa, Hazami, &

Farhat, 2013; Benli & Durmus, 2009; Chen et al., 2015, 2016; Kiyani, Bingol, Melikoglu, & Albostan, 2013; Sethi, Sumathy, Lee, & Pal, 2013; Sigrimis, Antsaklis, & Groumpos, 2001; Vadiie & Martin, 2012; Vanthoor et al., 2012; Yuan, Wang, Pang, Li, & Sigrimis, 2013). More specifically, for the case of solar greenhouses, heat transfer phenomena have been analysed, both theoretically (Liu et al., 2015) and practically, using computational models (Taki, Ajabshirchi, Ranjbar, Rohani, & Matloobi, 2016). Thus, several experimental studies have been conducted recently (Zhang, Fan, Liu, & Hao, 2016), leading to interesting applications of optimal utilisation of solar energy in such greenhouse structures (Khalid & Ammar, 2014; Sun et al., 2015).

Systems that are integrated with renewable energy sources and energy storage devices lead at best to short horizon predictive control schemes (Blasco, Martinez, Herrero, Ramos, & Sanchis, 2007; Coelho, Oliveira, & Cunha, 2005; Gruber et al., 2011; Van Straten, van Willigenburg, van Henten, & van Ooteghem, 2010), since the traditional reactive operation methods limit the possibility of exploiting long-term disturbance trends and of taking pre-emptory actions against potential emergencies (Coelho et al., 2005; Zavala et al., 2010). In addition, risk assessment for the severity and probability of damage caused by extreme weather could allow systems to respond more successfully (Troccoli, 2009), because both available and needed energy of SGHs are strongly dependent on weather. The evaluation and resolution of risk facing problems, such as unexpected weather extremes on structures with limited heating capabilities, is most effective if it involves appropriate application of three complementary elements: risk assessment, risk management, and market communication, the latter being needed as a “crop value expectation”. Risk assessment estimation by some weather probability margin (i.e. 10%) can be set by the user, but may be a dynamic value if the third element exists for off-line (smart SE design) and on-line (pro-active energy management) computations of cost-profit margins. These three components of the evaluation and resolution process address the understanding of the extent and magnitude of the potential crop production hazards, which in our case is based on an “expert” set of production function corner points, and may be upgraded to web-based Deep Knowledge Optimisation when complete production functions become available on the future Web hypermarket. More related studies, mainly for smart grid with high penetration of renewable energy, have been done based on mean-risk models in a two-stage stochastic programming framework, giving special consideration to weather-related operating risk (Varaiya, Wu, & Bialek, 2011) or price risk (Chakraborty, Shukla, & Thorp, 2011; Chu, Kaifuku, & Saitou, 2014; Mallor, Azcarate, & Blanco, 2009; Moazeni, Powell, & Hajimiragha, 2015).

This system is currently undergoing beta testing in the CAUA¹ system, based on MACQU (Management And Control for Quality, <www.geomations.com>) platform, developed by EU projects. The latter is used as an automaton ground-based CIMIC (Computer Integrated Management and Intelligent

Control) system (Sigrimis, 1999; Sigrimis, Hashimoto, Munach, & De Baerdmaeker, 1999). It is capable of interacting with web services for implementing “knowledge-based decisions”, that is, the most important and most valued component of production today and very critical in operating the SGH in cold regions. Knowledge (i.e. of plant requirements and specifically here the temperature response of plants) constitutes the vertical aspects of precision agriculture (Sigrimis, Antsaklis, & Groumpos, 2001), or more specifically in this study, precision horticulture, which raises the system higher in Knowledge Economy to contribute to “smart agriculture”. Sustainability sets decision criteria for “design and operation”, respects the smart specialisation principle and promotes the system from smart to “wise agriculture”.

Figure 1 shows three time-horizon based stages of the vertical precision aspects of the greenhouse control and management, based on the different time scales of the processes involved in a greenhouse cultivation system. The two inner loops have been implemented on the CAUA system and the new trials proposed in this paper concern the implementation of the outer loop (mainly as web services). When the system is fully tested in the simulated and experimental environment, the System Identification and Optimal Trajectory finder logic will be transferred in a ready-to-accept-the-logic web service (the FLOW-AID service belongs to the MACQU platform and is already being used for fert-irrigation and hydroponics optimisation over the web (Anastasiou, Savvas, Pasgianos, & Sigrimis, 2008)).

2. Materials and methods

2.1. Storage system design

Figure 2 shows the SGH equipped with active wall storage and SE system to meet the thermal requirements of plants, especially in cold winters.

The energy storage/retrieval process can be actively managed by controlling the heat exchange rate between the air and the storage devices, which can be described as:

$$Q = UA\Delta T, \quad (1)$$

where U is the heat transfer coefficient, A is the contact area, and ΔT is the temperature difference. The efficiency of heat exchange between the wall and the air can be increased by tubes installed in the wall to increase the contact area, and active control of the S/R fans to increase the heat transfer coefficient. With the heat exchange process controlled, surplus energy can be accumulated in the wall when input energy is greater than the plant needs, and retrieved to heat the air, in the opposite situation. Therefore, the northern wall can be used as an active energy storage with a wiser store/retrieve operation, targeting the best possible diurnal response for the plants, by a foreseen timely energy allocation, referenced to a balance for the forecasting period (3 days). Additionally, the SE system, composed, as an example, of a solar collector, a well-insulated water tank, and an elementary heat distribution system, is introduced to ensure crop safety during some possible short, winter extremes, designed and sized for a

¹ CAUA is a coalescence of the abbreviations of China Agricultural University (CAU) and Agricultural University of Athens (AUA).

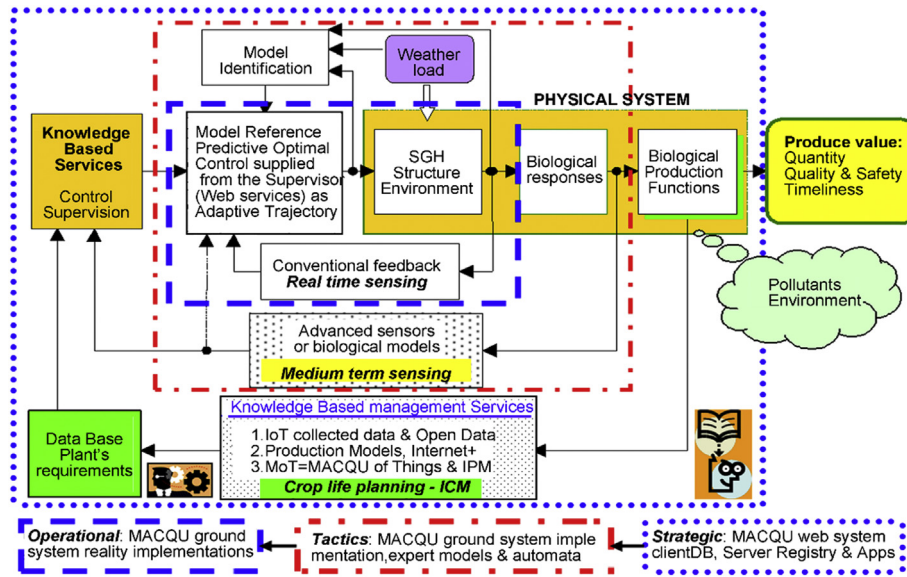


Fig. 1 – Multi-time-scale intelligent management and control of the smart-greenhouse environment.

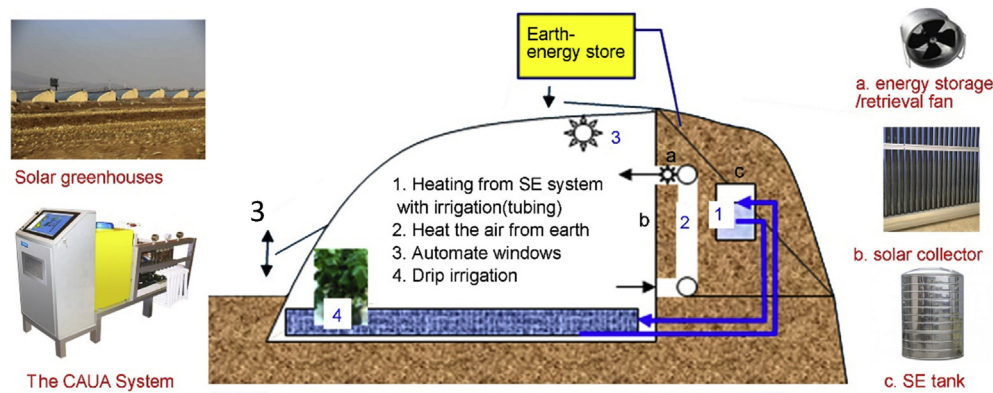


Fig. 2 – The SGH with active wall storage and SE system.

probable local weather. The described SE is a high “quality” energy source (water of 90 °C is of higher value than equivalent energy amount at 28 °C in the wall) which allows the difference to be used as risk supplement to the stored energy. Alternatively, any other local advantage of conventional type or renewable energy source, could also be used. The hot water in the tank, which receives its energy from the solar collector when solar radiation is available, was conceived here as “controlled reserves”, and it is sent to the heat distribution system, which may also have a number of innovative features, such as the conventional localised heating system (root heating, stem heating, etc.).

The accumulated energy in the storage devices can be described as:

$$E_{stor} = MC(T_{spare} - T_{Lim}), \quad (2)$$

where M and C are the mass and the specific heat capacity of the storage devices, respectively, T_{spare} is the temperature of the accumulator after being fully charged, and if temperature reaches T_{Lim} , which is the lower limit of the temperature,

energy retrieval is not allowed. The wall storage is charged by the redundant heat in the indoor air and retrieved to heat the indoor air, which means that the difference between T_{spare} and T_{Lim} of the wall is limited by the temperature of the indoor air. As for the SE system, which get energy directly from solar radiation by the solar collector, the T_{spare} of the tank water can be up to 90 °C. More importantly, with insufficient thermal insulation, some of the stored energy may leak to the outdoor air. The full thermal insulation of a small tank is easier and cheaper than the insulation of the entire northern wall for safety against rare extremes.

As discussed above, since the northern wall is an essential and supporting structure of SGHs, it is an effective and economical energy management mechanism for saving energy and improving productivity, with solely a small fan and wall tubing for active operation of wall storage, and a small constructive investment for regular weather conditions. For some winter extremes, such as several subsequent nights with very low temperatures, together with many days of insufficient solar radiation, the required storage of energy is

very high in calorific value; that is, the total energy needed for all the extremum nights must be stored and transferred from the sunny periods, as no heat energy is harvested during the extremum days. The SE system may be a more effective and operative solution with complete thermal insulation of the tank, but the installation of the SE system requires some additional investment, which may be justified under certain socioeconomic conditions. This concept of SE leads to a better optimal co-design of wall storage and SE together, to meet the infrequent lowest expected temperature winter conditions, which can be more economical than wall (crop risk) or SE (costly) alone. A weather evaluator pack (SGH designer) is under development for providing the best design at a given location (within the Smart Specialisation principles).

A 1 m long part of the SGH, which has a total length W (m), was taken as a sample for analysis, thus avoiding the end-effects of the east and west walls. The construction parameters of the SGH in the simulation study are shown in Table 1. More details of the model can be found in the previous work of Li, Li, Wang, and Sigrimis (2016).

2.2. Control logic

In our previous work on the proactive energy management of wall storage (Li et al., 2016), the climate control system was composed of three modules, as shown in Fig. 3: 1) the system identification module that updates the estimated system parameters and provides system properties to the model predictive controller; 2) the proactive energy management module finds the optimal temperature trajectory for a planning period ahead taking account of weather forecasts (taken as three days in this analysis); 3) the controller computes and applies the controls on the simulated and the physical system of the SGH for tracking the selected trajectory in the next timeslot, sampling the new measurement vector sample for modules 1) and 2) to re-compute and update again the full length trajectory. That is, every 10 min the system takes a sample measurement vector, applies the computed controls for the next 10-min period, and computes the full 72-h trajectory to be applied during the next sample period. Based on that physical system, we applied the risk assessment for the SE system to compensate for the risk that the operation of wall storage fails to meet the demand in the extreme weather cases.

In this paper, in addition to the wall acting as a sustainable primary energy source to meet the regular energy needs, we introduce the special SE, composed of solar collectors

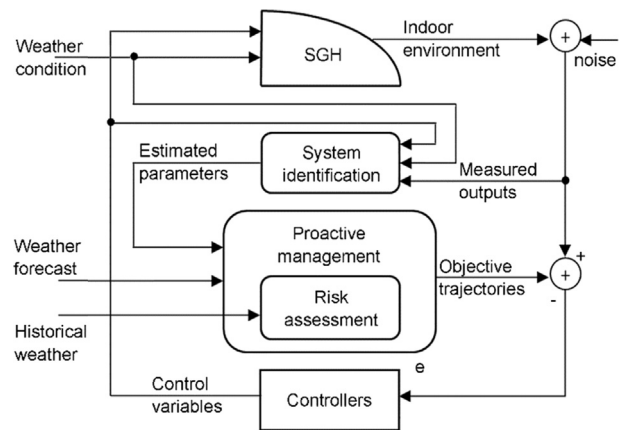


Fig. 3 – System framework for the proactive energy management and risk minimisation.

connected to a well-insulated storage tank and ground tubes, acting as a supplement to the primary energy source for normal weather conditions, and as an insurance against unpredictable extreme weather conditions. The innovation here is that, in cases of winter temperature extremes and lack of solar radiation, the required storage is very big in calorific amount, which can be harvested over a long period, and delivered quickly. This special character of security heat source necessitates the economical co-design of these two different storage devices, as well as the optimal management of their dynamic cooperation, which allows the minimisation of crop damage and risk, with minimum storage media investment. A “cost-risk” computational model in a two-level scheme is applied in the optimisation process; however, we assess the risk value based on a probable worst weather under certain likelihood instead of the expectation, by Monte-Carlo sampling in two-stage stochastic programming (Moazeni et al., 2015; Schultz & Tiedemann, 2006; Zhou et al., 2013), to avoid the heavy computation. The simulation demonstrates that the risk that the wall energy proves to be insufficient to secure against an unexpected extreme weather, can be minimised by the management of the SE system. That is, the wall and the SE system operate similarly, with the SE complementing the wall stored heat, while SE reserves a sufficient amount to meet a potential extreme at the 5% probability level drawn from 10 years past historical weather open data.

With the optimal co-design of the wall and the SE system, it is also important to develop an effective policy to manage their dynamic cooperation. The ways to calculate the control signals of the storage devices are defined in the following paragraph. The control logic for other devices, such as the curtain and ventilation, can be found in our previous work (Li et al., 2016). With the aim to avoid energy loss in cold winter periods, the SGH is closed without ventilation, so the set-point for window controls is not considered in this work.

For the operation of wall storage, u_f is the control input (PWM) for the S/R fan calculated by a PID controller keeping indoor air temperature (T_i) at set-point T_{is} for energy storage or T_{ir} for energy retrieval. Obviously, only when T_i is higher than the wall temperature (T_w), can the heat in the air be transferred and stored into the wall. Under this condition, if $T_i > T_{is}$,

Table 1 – Parameters in the simulated SGH per 1 m analysis sample length.

Parameter	Values
Height of the SGH	3.5 m
Width of the SGH	10 m
Thickness of the wall	0.5 m
Thickness of the insulation	0.1 m
Thickness of the curtain	0.03 m
The diameter of the pipes in wall	0.1 m
The volume of the SE tank	0.02 m ³
Solar harvesting collector surface	0.3 m ²

the S/R fan is turned on for energy storage and reducing T_i to T_{is} . Similarly, energy retrieval can only happen if $T_i < T_w$. Based on that, when $T_i < T_{ir}$, the energy is retrieved from the wall to maintain T_i by the S/R fan until T_w decreases down to T_i which means the wall storage has been used up.

To deal with the extreme weather, the SE storage is utilised according to set-point T_{iSE} . When $T_i < T_{iSE}$, the heat exchanger, controlled by u_{SE} (PWM), is turned on to send the hot water to the heat distribution system, until solar radiation is available, to raise T_i up to T_{iSE} or the water temperature in the tank (T_t) falls to the lower limit, preventing overuse. To sum up, the flowchart of the operations is depicted in Fig. 4. Smartness here refers to when to trigger each operation to allocate the energy with a final target of best plant productivity while cold stress safety is guaranteed. Thus, the selection of the set-points is crucial for the optimal utilisation of energy. For example, more spare energy is supposed to be stored in the SE tank and in the wall by decreasing T_{ir} , T_{is} and T_{iSE} when the weather forecast indicates worse weather conditions coming.

2.3. The proactive energy management

Reactive control strategies update operational decisions based only on current information of disturbances, such as weather conditions. This lack of pro-activeness limits the possibility of exploiting long-term disturbance trends and of using storage components optimally (Zavala et al., 2010). In the proactive energy management, the optimal set-points are optimised for a longer planning period based on model predictive control, of which the efficiency and security are closely related with the accuracy of energy supply and demand prediction, both heavily dependent on the weather forecast (temperature, solar radiation and wind speed). As time passes, the probability and severity of deviation in the prediction increases (Mallor et al., 2009). Although only the control signals of the current timeslot are applied to the system, which allows

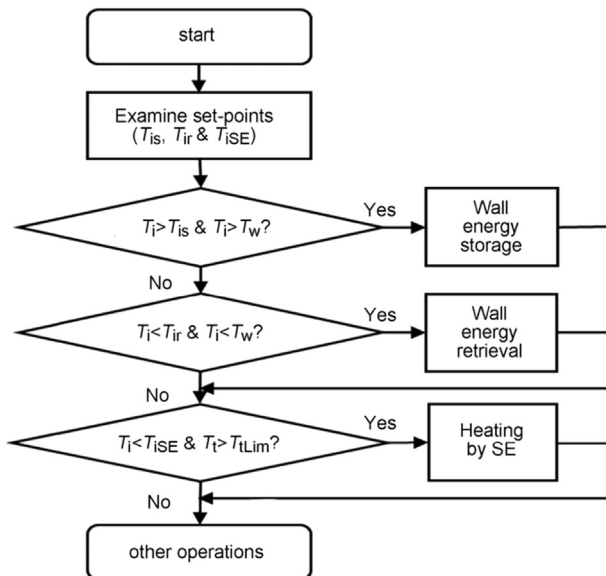


Fig. 4 – Flowchart of the proactive energy management, conditions-actions.

timely utilisation of a more recent forecast for regularly optimised control pro-actions, we have further improved its tolerance to the uncertainty in the weather forecast, by optimising the storage operation with a weather-related risk measure in a two-level control scheme.

2.3.1. Uncertainty in weather prediction

For each locality, we can draw on important weather statistics, if data exist, and apply them to the forecast expected average or peak points, to produce probabilistic weather predictions for three or seven days ahead. A widely-used model in stochastic programming, which could deal with the uncertainty in weather predictions, is the expectation-based model (Schultz & Tiedemann, 2006; Zhou et al., 2013). However, it requires heavy computation to approximate the mathematical expectation by repeated random sampling in the Monte-Carlo simulation. Instead, in this paper, we simply define the band of 95% weather probability and use the extreme conditions of that band to compute deterministically the conservative risk in respect to SE management.

An example of probable temperature prediction is shown in Fig. 5, with the expected minimum/maximum temperature trajectories as the most probable trend, and the shaded deviation under a certain likelihood level (i.e. weather zones of 95% probability etc.). The solid black line is the expected temperature trajectory for cost value evaluation and the dashed black line is an extreme temperature trajectory for risk assessment. These trajectories are generated according to the expected maximum/minimum trend and probable maximum/minimum trajectories in the weather zones, respectively, by peaking at the maximum at 14:00 and dropping to the minimum at 6:00. The peak time varies with the changing seasons and the local latitude.

2.3.2. Model for predictive control

For choosing the optimal set-points in the planning period, a model is needed to predict the resulting thermal environment inside the SGH varied with the candidate set-points and the weather condition, which can be defined as in Equation (3).

$$\begin{bmatrix} T'_i \\ T'_w \\ T'_{soi} \\ T'_t \end{bmatrix} = P_1 \begin{bmatrix} T_i \\ T_w \\ T_{soi} \\ T_t \end{bmatrix} + P_2 \begin{bmatrix} u_c \\ u_f \\ u_v \\ u_{SE} \end{bmatrix} + P_3 \begin{bmatrix} T_o \\ V_{wd} \\ I_{rad}(1 - u_c) \\ I_{rad}F_t \end{bmatrix} \quad (3)$$

The model outputs are the predictive system status at the next timeslot, including the average (representative)

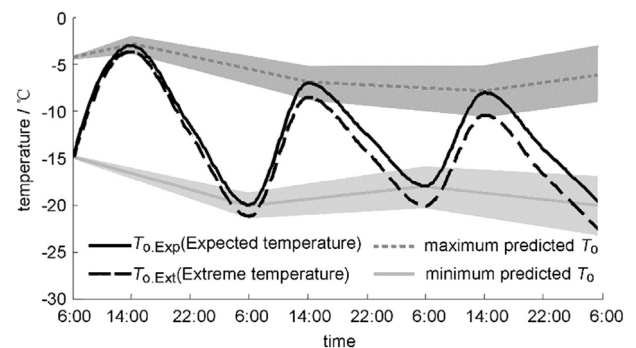


Fig. 5 – Temperature prediction with uncertainty.

temperatures of the indoor air (T_i), the wall (T_w), the soil (T_{soil}) and the water in the SE tank (T_s), respectively, as the determining factors of crop stress and thus the objects of analysis and control. The model inputs can be grouped into three vectors as previous states, control inputs and disturbance variables, weighted by parameters (P_1 , P_2 and P_3) found by on-line system identification with pre-process of input linearisation (Li et al., 2016). The control inputs of the ventilation (u_v), the curtain operation (u_c), the S/R fan (u_f) and the SE system (u_{SE}) are computed according to the set-points. The uncontrollable inputs or disturbance variables are calculated according to the weather conditions, i.e. outside temperature (T_o), solar radiation (I_{rad}) and wind speed (V_{wd}).

The solar radiation is the energy source for both the SE tank and the indoor air. Therefore, for linearisation of the model, we introduced two disturbance variables about solar energy harvest correspondingly: u_c indicates curtain's position; $u_c = 0$ when curtain is completely rolled up; $u_c = 1$ when curtain is completely rolled down. The variable $I_{rad}(1 - u_c)$ is the solar energy harvest through the cover which may be zero when the curtain is rolled down ($u_c = 1$) to block the sun light, and $I_{rad}F_t$ relates to the solar energy charging the SE tank, where F_t indicates whether the SE tank is full or not: if $T_t \geq 90^\circ\text{C}$, then $F_t = 0$ and the tank is full, while if $T_t < 90^\circ\text{C}$, then $F_t = 1$ and the tank can be charged.

2.3.3. Optimisation problem

The mathematical control problem here is to find the optimal operation set-points for a given set of weather conditions by minimising the objective function J , related to crop stress, over the planning period. We formulated the optimisation problem as a master problem in combination with a sub-problem. Figure 6 shows the two-level optimisation scheme with the detailed processes of cost value calculation and risk assessment. The operation of the wall storage is found in the master level to minimise a cost value with the expected weather. Respectively, the SE system management, as a sub-decision under extreme weather, is optimised according to a risk value, to prevent crop total loss as its primary purpose and then supplement the limited wall storage for a better indoor thermal environment when the risk for extreme weather allows an amount of SE spare energy to be used.

Operation set-points of storage devices are divided into two groups: T_{ir} (retrieve wall energy) and T_{is} (save wall energy) set in a symbolic vector T_{iw} for wall storage operation; and T_{iSE}

for the SE storage system. The sub-problem optimises T_{iSE} to minimise the risk value with a candidate T_{iw} set by the master problem. T_{iw} is searched in the master problem to minimise the weighted sum of the cost value and the risk value, of which the cost value is calculated with T_{iSE} set to be ϵ ($\epsilon > 0$) above T_{cTL} for preventing total loss in all cases, and the risk value optimised by the sub-problem.

The objective function is split into two terms: J_C is the cost function of the expected weather (ω_{Exp}), and J_R is the risk function of the extreme weather (ω_{Ext}). The optimisation problem is given by:

$$\text{(master): } \min_{T_{iw}} J = \min_{T_{iw}} \{ \alpha J_C(T_{iw}, \omega_{Exp}) + \beta J'_R(T_{iw}, \omega_{Ext}) \}, \quad (4)$$

$$\text{(sub): } J'_R(T_{iw}, \omega_{Ext}) = \min_{T_{iSE}} J_R(T_{iw}, T_{iSE}, \omega_{Ext}). \quad (5)$$

In the sub-problem, T_{iw} is assumed to be fixed as a candidate master-decision. Therefore, it is a computing-power consuming process, as for each T_{iw} in the main search space, the space of T_{iSE} needs to be searched; α and β are the parameters balancing the risk and cost value, characterising a risky user, who defines the α and β parameters.

The optimisation problem can be solved by a hybrid evolutionary algorithm (Schultz & Tiedemann, 2006), with a genetic algorithm (GA) (Gutin & Karapetyan, 2010; Valls, Ballestin, & Quintanilla, 2008) addressing the master problem. The principles of GAs are well known: the algorithm starts with a population of randomly generated solutions (individuals with various chromosomes determining sets of properties) which are selected according to their fitness, and evolve towards better solutions by crossover and mutation; this generation process is repeated until a termination condition has been reached, with the fittest individual as the solution to the optimisation problem. Figure 7 is the flowchart of the optimisation problem solved by a hybrid evolutionary algorithm.

2.3.4. The objective function

The objective function, evaluating the chosen set-points, indicates the crop stress caused by unfavourable high or low indoor temperature. Some corner points of plant production function temperature sensitivity, provided by some expert knowledge on the specific cultivar or determined by a web service supervising the SGH operation and linked to breeders' announcements, are introduced here, and illustrated in Fig. 8.

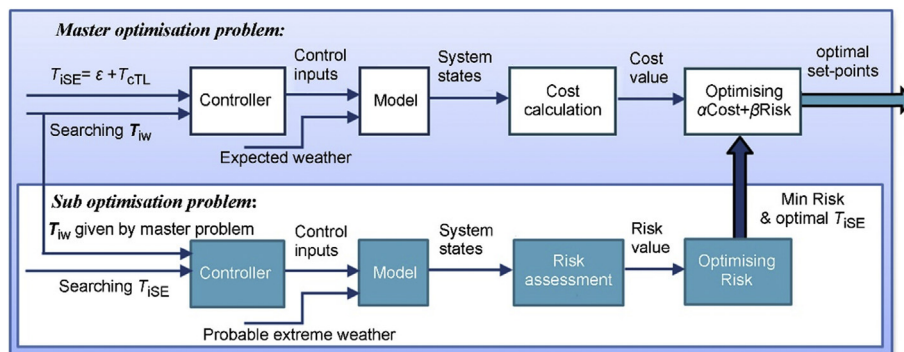


Fig. 6 – Two-level optimisation scheme with cost value calculation and risk assessment.

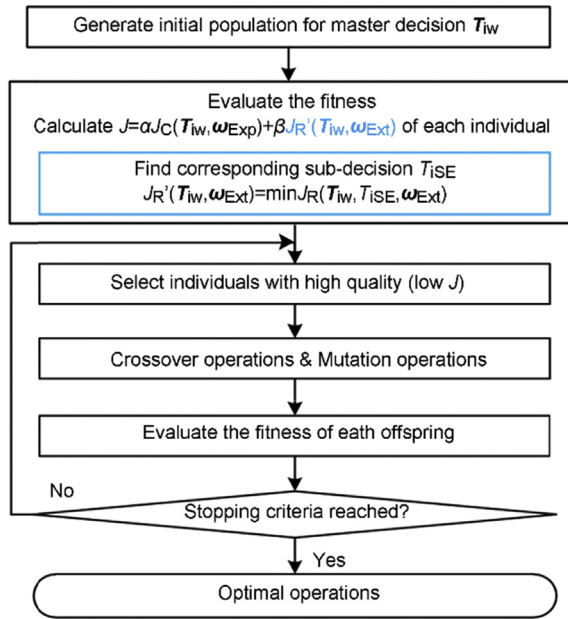


Fig. 7 – Flowchart of optimisation problem solved by a hybrid evolutionary algorithm.

Although, in this paper, the inside temperature $[T_{\text{clow}}, T_{\text{chigh}}]$ is supposed to have a similar influence on plant growth, the gap between $[T_{\text{clow}}, T_{\text{chigh}}]$ is something that provides an additional freedom to improve energy management, and may be determined based on plant sensitivity and production price. If the yield and price are given by a production and market model, the Pontryagin's maximum principle can be used (Van Straten, van Willigenburg, & Tap, 2002) for the development of a self-guided decision support system (deep knowledge) (Li, Sigrimis, Anastasiou, Wang, & Patil, 2012, Fig. 3) rather than expert advice acquired or stored (shallow knowledge) that we prefer here.

According to the plant sensitivity points, some functions that indicate crop loss for the planning period N based on indoor temperature trajectories as inputs, are set as follows:

$$\begin{aligned} L_{\text{hl}}(T_i) &= \sum_{n=1}^{n=N} W_{\text{hl}} [T_i(n) - T_{\text{chigh}}]_+^2, \\ L_{\text{cl}}(T_i) &= \sum_{n=1}^{n=N} W_{\text{cl}} [T_{\text{clow}} - T_i(n)]_+^2, \\ L_{\text{TL}}(T_i) &= \sum_{n=1}^{n=N} W_{\text{TL}} \left([T_i(n) - T_{\text{cTL}}]_+ + \delta \right)^{-2}, \end{aligned} \quad (6)$$

where function $[\cdot]_+ = \max(\cdot, 0)$, and all the weights are non-negative variables. L_{hl} indicates the high temperature crop

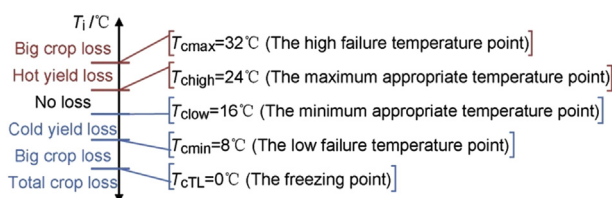


Fig. 8 – Segmented temperature range and the plant sensitivity points.

loss, heat stress and disease risk when $T_i(n) > T_{\text{chigh}}$, weighted by W_{hl} . Similarly, L_{cl} indicates low temperature crop loss, cold stress and disease risk when $T_i(n) < T_{\text{clow}}$, weighted by W_{cl} . L_{TL} presents the serious loss, drastically rising when T_i drops near T_{cTL} , weighted by W_{TL} . δ is a small value preventing the denominator being equal to zero.

Furthermore, for optimising the SE utilisation, we introduce a variable L_{SE} for the loss of the SE, calculated using the water temperature in the SE tank (T_t):

$$L_{\text{SE}}(T_t) = \sum_{n=1}^{n=N} W_{\text{SE}} \left([T_t(n) - T_{\text{tLim}}]_+ + \delta \right)^{-2}, \quad \text{if } T_t(n) < 90^\circ\text{C}, \quad (7)$$

where W_{SE} is the weight for the risk that SE is overused; T_{tLim} is the limit for the water temperature of SE, such that, when $T_t \leq T_{\text{tLim}}$, the SE cannot provide any heat energy to the greenhouse.

In the objective function, with the set-points as the input values, the control signals can be calculated according to the control logic; after that, the system's states (i.e. indoor air temperature, wall temperature and water temperature in the SE tank) corresponding to the candidate set-points, can be predicted based on the model, and thus the crop stress for the planning period is minimised.

The set-point for wall energy management (T_{iw}) is found by minimising the cost value, regardless of any probable errors in the weather prediction. Therefore, the cost value is calculated based on predictive air temperature (T_{iExp}) and predictive wall temperature (T_{wExp}) determined in the prediction run, with expected weather ω_{Exp} and $T_{\text{iSE}} = \epsilon + T_{\text{cTL}}$ ($\epsilon > 0$) in the model. Calculated by the function f_C as below, the cost value relates to the estimation of the heat loss (L_{hl}), cold loss (L_{cl}) and the remained wall energy storage.

$$f_C = L_{\text{hl}}(T_{\text{iExp}}) + L_{\text{cl}}(T_{\text{iExp}}) - W_{\text{ws}} T_{\text{wExp}}(N), \quad (8)$$

$T_{\text{wExp}}(N)$ is the expected wall temperature of the last sample in the predictive horizon. W_{ws} , the weight for wall storage, is the energy value normalisation factor that is positively affected by the wall thermal capacity and may be inversely affected by the greenhouse insulation quality, the weather and crop stage context. Higher W_{ws} drives the system to be more conservative, indicating that the energy stored values are more important, in relation to yield loss. In conclusion, the stress on crops is diminished by minimising f_C , which is inversely affected by the energy stored in the wall for the following days, as it is the value of the final state of control.

Similarly, the optimal set-point of the SE system is found by minimising the risk value. Based on the probable extreme weather (ω_{Ext}), the predictive air temperature (T_{iExt}) and predictive tank water temperature (T_{tExt}) can be predicted, with the set-points T_{iw} given by the master problem and T_{iSE} as the input. These predictions can be used to assess the crop stress under risk. Besides the heat loss (L_{hl}) and cold loss (L_{cl}), the function f_R also takes into consideration the consumption of SE (L_{SE}) and the total loss (L_{TL}), to create a balance between loss due to low T_i with possible frost, and overuse of the SE:

$$f_R = L_{\text{hl}}(T_{\text{iExt}}) + L_{\text{cl}}(T_{\text{iExt}}) + L_{\text{TL}}(T_{\text{iExt}}) + L_{\text{SE}}(T_{\text{tExt}}) \quad (9)$$

3. Results

The weather forecast period N is three days and the sampling interval is 10 min. For the sake of analysis, the optimal set-points (trajectories) are updated every day in this test (similarly to having a new forecast every day by Open Data capture), instead of every timeslot. The parameter values in the objective function are: $W_{hl} = 0.01$; $W_{cl} = 0.01$; $W_{TL} = 10$; $W_{ws} = 0.1$; $W_{SE} = 0.01$. These of course, together with the crop corner points, need be tuned to approximate a real nonlinear crop sensitivity production function.

3.1. The performance of the controller

Figure 9 shows how the curtain u_c , the S/R fan u_f and the SE pump u_p work according to the weather condition and prediction. As shown in Fig. 9, the curtain is operated based mainly on the amount of solar radiation, and is rolled down ($u_c = 1$) for better thermal insulation at nights, and rolled up ($u_c = 0$) to let more solar energy be absorbed in the SGH, activated when radiant energy entering is higher than the convective heat loss through the plastic cover. The S/R fan (u_f), operated by a PID controller, tries to keep T_i at T_{br} or T_{bs} . However, because of the

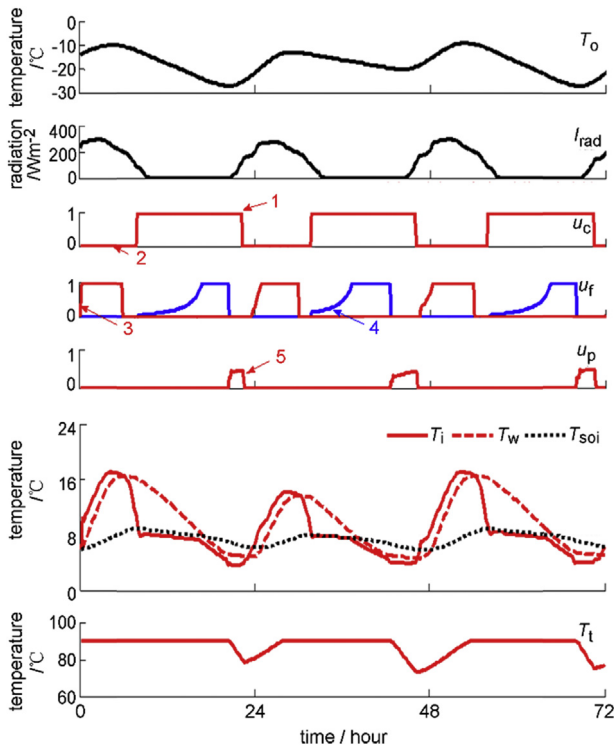


Fig. 9 – Performance of control strategies in a typical cold weather in Chaoyang-Liaoning. Letter marks (u_f , u_c , u_p , T_i , T_w , T_{soil}) on figure lines are defined in Nomenclature Table. Number marks on lines are as follows: Point 1: curtain roll-down action for insulation at nights; Point 2: curtain roll-up action for harvesting solar energy; Point 3: S/R fan operation for wall energy storage (red line); Point 4: S/R fan operation for wall energy retrieval (blue line); Point 5: SE operation (u_p affecting T_i) to supplement heat and avoid severe cold stress.

large energy income from sufficient solar radiation and the relatively small heat exchanger capacity between the air and the wall (no need to overdesign the wall tubing), T_i cannot be stationary at T_{bs} during the energy storage, and u_f is fully operated ($1 =$ saturated controls) in those cases. On the other hand, the limited energy in the wall keeps T_i stable as long as T_w is sufficient, and it drops along with T_w during the energy retrieval process, up to the point that T_t may take charge. The SE pump (u_p) works to retrieve the SE to maintain a stable T_i at T_{ise} above the frozen point, minimising the risk values. Furthermore, the performance of ventilation (u_v) is not examined and discussed in this paper, but more tests can be found in our previous work (Li et al., 2016).

3.2. The performance of the SE system

Specific cold days were selected to show the way that the wall storage and the SE system profoundly affect the minimisation of the plant cold stress. During those days, daily average temperature was -20 °C and maximum solar radiation was 280 $W\ m^{-2}$. Two simulation tests were run with proactive energy management, in two SGHs. One of the SGHs (identified as “SEW”), was equipped with wall storage and the SE system. The other SGH (identified as “W”), was equipped with only the wall, with the same thickness and thermal properties. Figure 10 shows the comparison of the air temperature trajectories in the two SGHs.

For quantitative analysis of the simulation results, as shown in Table 2, we introduce two variables to examine the performance of the management method. A loss value, including the heat loss, cold loss and the total frozen loss, as defined in Equation (6), is defined as follows:

$$L(T_i) = L_{hl}(T_i) + L_{cl}(T_i) + L_{TL}(T_i). \quad (10)$$

In addition, we define a performance climate-quality indexing function $g(t)$ with regards to the plant productivity environment. The $g(t)$, related to the required SE, is the negative degree hours area (°C h) enclosed by the temperature curve T_i and the line of $y = T_{cmin}$, and is defined in Equation (11):

$$g(t) = \sum_{k=1}^{k=K} \int_{t_{stt}(k)}^{t_{end}(k)} [T_i(t) - T_{cmin}] dt \quad (T_i(t) < T_{cmin}), \quad (11)$$

where K is the total number of the pieces of time periods in which T_i is lower than T_{cmin} , with $t_{stt}(k)$ and $t_{end}(k)$ respectively as starting point and end point of the time piece k ($k = 1, 2, \dots, K$). This $g(t)$, as defined in Eq. (11), represents the energy (if multiplied by the lumped energy loss factor) needed to avoid harmful effects on plant production or first level cold stress (below T_{cmin}). In the future, we will define it together with a short time average of T_i (T_{iavg}) in order to move at the margins of stress tolerance, as defined by the plant temperature integration potential (Sigrimis, Anastasiou, & Rerras, 2000).

As shown in the results, the longer the extreme weather lasts, the more advantages the SE system can provide to the SGH, given it is sized enough for the particular weather case. Most significantly, the minimum temperature was improved by the introduction of the SE system, which proved that the

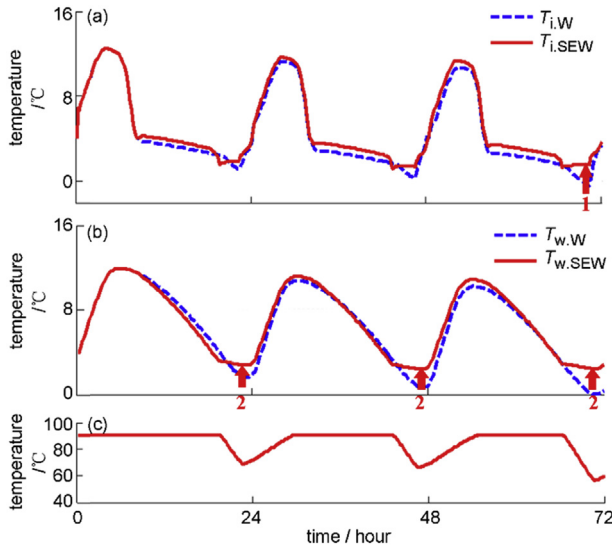


Fig. 10 – Temperature trajectories in SGHs with and without the SE system: (a) indoor air temperature (T_i) with wall storage ($T_{i,W}$) and with both wall storage and SE ($T_{i,SEW}$); (b) wall temperature with wall storage ($T_{w,W}$) and with both wall and SE ($T_{w,SEW}$); (c) SE tank water temperature. Point 1: Avoiding frost (total loss) by SE; Points 2: Saving more wall storage ($T_{w,SEW}$) and better $T_{i,SEW}$ (1) with SE as supplement.

Table 2 – Detailed statistics of the results in SGH with and without the SE system.

Test	Highest $T_i/^\circ\text{C}$	Lowest $T_i/^\circ\text{C}$	Average $g(t)/(^\circ\text{C h})$	$L(T_i)$	
W (only wall)	12.56	-0.39	4.61	-287.00	9439.50
WSE (wall & SE)	12.56	1.18	5.09	-257.83	1037.20

energy (of any kind, but available when needed) can be used to prevent total loss of the crops caused by the limited wall storage and insufficient harvested energy that fails to keep the indoor air temperature above a target point. Our effort is to maintain the solar character of the greenhouses and provide solutions that can be sustainable in all aspects of environment and socio-economics. Furthermore, in this test, the wall temperature ($T_{w,SEW}$) and the chosen set-points for wall energy retrieval ($T_{br,SEW}$) in the SGH with the SE system, were increasingly higher than $T_{w,W}$ and $T_{br,W}$ in the SGH with the wall as the only active storage device. This indicates that accumulated spare energy can remain in the wall with the SE as supplement, available to be retrieved for a better indoor thermal environment for a longer time, based on the proactive energy management.

3.3. The performance of the proactive energy management with risk assessment

Some experiments that test different operation policies were carried out, based on some special cases of interest, i.e. cold and warm weather, with the same curtain operation based on the energy balance through the cover. The different operation

policies for the co-management of the wall storage and the SE system were defined as follows: 1) operation by proactive energy management, identified as experiment “P”; 2) operation with fixed set-points ($T_{is,F} = T_{clow} = 16^\circ\text{C}$, $T_{ir,F} = T_{clow} = 16^\circ\text{C}$, $T_{iSE,F} = T_{CTL} = 0^\circ\text{C}$), identified as experiment “F”; 3) non-operation, identified as experiment “N”. Specific winter days (Day 1, Day 2 and Day 3) were selected to demonstrate, for each case, how the operation policies have different effects on the indoor thermal environment. Some information on the weather and the chosen set-points by proactive management of each day are shown in Table 3. Figure 11 shows the test results and Table 4 presents some detailed statistics.

It’s obvious that the worst performance was $T_{i,N}$, generated without active wall storage and the SE system. As shown in Table 4, the installation of SE system, the S/R fan and in wall tubes can achieve, as expected, a better thermal environment inside the greenhouses for the plants, mainly by preventing the indoor air temperature from falling towards the freezing point. In addition, the proactive energy management further improved the loss value by a better time-allocation of the energy. All these will be refined by taking into consideration the temperature integration of each plant species to provide a better holistically justified overall SGH modern design, inclusive of other justified automated equipment like ventilators, screens and cooling for the summer operation.

The set-points and their resulting thermal environment for the proactive energy management and the management with fixed set-points, are compared and analysed below. On Day 1, the process of wall energy storage was proved to have a good effect on decreasing heat stress by transferring the heat from the air into the wall with the S/R fan instead of ventilation. Furthermore, because of the adequate solar energy in the upcoming days which could recharge the SE tank, the proactive energy management chose a higher set-point for SE operation for Day 1 to use the SE as the supplement to wall storage for a warmer indoor environment above T_{cmin} at night. This also kept more spare energy stored into the wall.

The comparison between $T_{i,P}$ and $T_{i,F}$ on Day 2 showed that the proactive energy management can use the wall storage more effectively. It was attributed to the increased spare energy stored on Day 1 and a lower $T_{bs}(2)$ to allow more energy to be stored into the wall and a lower $T_{br}(2)$ for a wiser utilisation of the wall energy. Despite the fact that the fixed set-point (higher than the chosen ones) controls the S/R fan to retrieve the energy earlier to keep $T_{i,F}$ closer to the optimal temperature at the beginning, $T_{i,F}$ drops to a lower point more quickly, due to the shortage of the limited wall storage, while $T_{i,P}$ can be maintained in the suboptimal range for a longer time.

Table 3 – The weather and the chosen proactive set-points of each day for SGHSE.

Parameters	Day 1	Day 2	Day 3	
Average $T_O/^\circ\text{C}$	-5.0	-13.0	-20.0	
Maximum $I_{rad}/(\text{W m}^{-2})$	220	300	230	
Set-points/ $^\circ\text{C}$	T_{bs}	$T_{bs}(1) = 9.60$	$T_{bs}(2) = 7.46$	$T_{bs}(3) = 7.95$
	T_{br}	$T_{br}(1) = 16.51$	$T_{br}(2) = 12.41$	$T_{br}(3) = 11.36$
	T_{bSE}	$T_{bSE}(1) = 8.98$	$T_{bSE}(2) = 5.92$	$T_{bSE}(3) = 5.54$

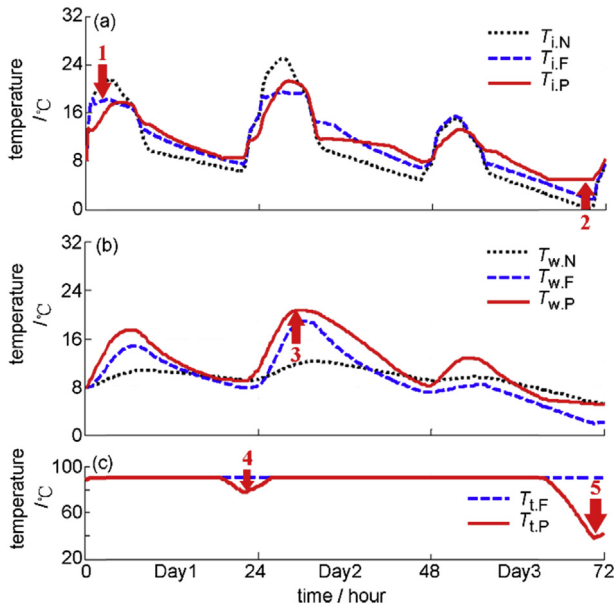


Fig. 11 – Simulation results with different management policies: (a) indoor air temperature with no active operation ($T_{i,N}$), with fixed set-point management ($T_{i,F}$) and with proactive energy management ($T_{i,P}$); (b) wall temperature with no active operation ($T_{w,N}$), with fixed set-point management ($T_{w,F}$) and with proactive management ($T_{w,P}$); (c) SE tank temperature with fixed set-point management ($T_{t,F}$) and with proactive management ($T_{t,P}$). Point 1: Reducing heat stress with active storage; Point 2: Reducing cold stress with active retrieval; Point 3: Harvesting and saving more wall energy; Point 4: SE surplus energy made useful as spare supplement in addition to regular wall energy supply for better T_i ; Point 5: SE as safety heat supply under extreme weather.

Table 4 – Detailed statistics of the simulation results showing proactive with SE advantages.

Test	Highest $T_i/^\circ\text{C}$	Lowest $T_i/^\circ\text{C}$	Average, $g(t)/(^\circ\text{C h})$ $T_i/^\circ\text{C}$	$L(T_i)$	
N	25.06	0.27	10.03	-100.42	1561.70
F	19.51	1.75	10.93	-56.84	400.94
P	21.34	4.92	11.25	-28.67	262.41

On Day 3, the weather is in the extreme cold region, and the solar radiation is insufficient. The SE system showed its advantages by successfully preventing total loss near the freezing point, given that during the next day (Day 4), it would be able to recharge. Of course, this is the case if the 3-day old weather predictions are still valid at that point. If the conditions have changed unpredictably, the Proactive system will adapt accordingly.

3.4. Impact of weather forecast error

The impact of probable errors in weather forecast on the crop stress was examined. For analysing stochastic prediction errors, 100 Monte-Carlo simulation runs were carried out with a normal distribution (standard deviation equal to 10%) added

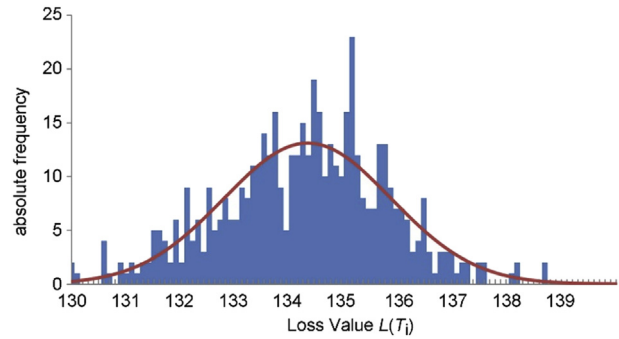


Fig. 12 – Distribution of loss value of the system with wall storage and SE system for 10% forecast errors in weather prediction.

to the weather conditions. Figure 12 shows the distribution of loss value, as the performance in the proactive energy management of the dynamic cooperation of the SE system and wall storage, for the simulation tests over a time period of 24 h. This histogram can be approximated by a normal distribution (the line curve on the graph). Table 5 presents the comparison of the impact of forecast errors, i.e. the average value and the standard deviation (std) of the loss value, between the SGH with only wall storage (SGHW) and the one with both wall storage and the SE system (SGHSEW).

The average loss was reduced by the installation of the SE system. The deviations of 10% within the weather forecast were minimised by the storage devices and the proactive energy management methods. Compared to the SGHW, the SE system, which was operated according to the risk assessment, can further reduce the standard deviation of the loss value from 2.1, corresponding to 1.5% of the mean value, to 1.52, corresponding to 1.1% of the mean value. Although the risk management is based only on one typical case of probable extreme weather instead of the probable distribution of weather, the Monte-Carlo simulation shows its great tolerance of the forecast errors for most of the cases. It should be pointed out that the selected sizes (and required costs) of W and SE performed well for the given weather low T_o extreme case studied here. Of course, sudden extreme weather cases are expected to be included in the forecast deviants of each regional weather, so that the optimal SGH designer (under development based on this smart energy management program), would properly consider sizing each of W and SE storages based on economics of investment versus produce value.

Further improvement of the cost function can be realised by additionally taking into account air humidity, as well as other pest related issues, which would also need a complete greenhouse climate model to control ventilation and apply

Table 5 – Comparison of tolerance to forecast errors between SGH with and without SE system.

Items	Average $L(T_i)$	Std of $L(T_i)$
SGHW	141.77	2.10 (1.5% of average $L(T_i)$)
SGHSEW	134.21	1.52 (1.1% of average $L(T_i)$)

IPM production rules or even pest bio-behaviour as virtual reality or avatars (Li et al., 2012, Fig. 2).

4. Conclusion

A novel energy management method was developed for long time-horizon energy utilisation and potential crop stress minimisation by selecting an optimal SGH trajectory for a forecasted weather period, in accordance with “expert”-defined plant behaviour. It includes a) a proactive energy management module that modifies the energy storage/retrieval process for better time-allocation of stored energy to meet projected demand, and b) a risk management module, using optimally the SE storage based on the probabilistic extreme weather forecasts along with the local weather characteristics based on past 10-year recorded statistical behaviour. The results demonstrate that the proactive logic module offers a substantial improvement on low temperature stress minimisation, by looking ahead at forecast weather and fitting a heat balance temperature trajectory that maximises plant performance. A sustainable greenhouse starts from optimal design (wall thickness, insulation grade, SE size) for the specific local weather, and the advantages offered by proactive operational practice. The rational sizing between wall and SE storage depends on the low temperature peaks, their extreme peak, the degree-hours duration, and frequency of occurrence. It proves that the addition of SE not only improves the temperature performance, but also may lead to less total cost than designing a solely active wall viable structure. The system, in the form of a web client support service, is currently being tested on the CAUA system (a supervisory control and data acquisition system) to enhance the energy sustainability of not only SGHs, but conventional energy glasshouses as well.

The simulation study shows that the proactive energy management can be used for energy saving while keeping greenhouse air temperature within desired limits. An example showed that the minimum temperature can be improved from 0.27 °C to 1.24 °C by adding a simple active heat storage facility (fan) and further improved to 4.92 °C by adding a SE system of minimal initial investment and co-operated by the proactive management logic. In addition, the SE showed its ability to cover the energy demand economically for less probable extreme weather conditions. It has also shown great tolerance of forecast errors in most cases, which greatly improved the performance of the greenhouse for sustainable production, dependent solely on solar energy. With the proposed method, SGH design can achieve a Locally Smart Specialisation, which we are advancing to a “Regional Weather Evaluator for SGH Design – smartWE”.

The system is tuned for transferring the high-level processes to a web service for clients of SGHs, as well as to be open to communicate with and receive data from other web services that are currently at development stage (Open Data), such as market price predictions and micro-scale weather forecasts. This kind of operating mode is advancing the IoT modern approach for a web-based hypermarket that can provide practical benefits to producers and consumers. Future work focuses on improving performance by combining the

smart energy management with plant production models, and developing a wise weather and market evaluator for SGH construction design, based on relevant regional weather and market information. When this is tied to production and market parameters for each vegetable species, it will push the limits of “Smart Specialisation”, that is becoming a modern requirement and a sustainability necessity. Smart energy management systems are becoming of outmost importance in today’s competitive world, which in this case is, a holistic service offered “from Design to Operations of Sustainable (DOS) modern Solar Greenhouses”.

Acknowledgements

This research was supported by the National Natural Science Foundation for Young Scholars of China (Grant No. 31301240) and the open project of State Key Laboratory of Soil-plant Machinery System Technology (Grant No. 2014-SKL-03). The authors are thankful to Professor Maohua Wang (member CAE), the leader of the team for solar greenhouse closed cultivation system supporting the societal challenges of giving returns to People from research investments. The basic MACQU technology has been developed through several European and Greek-China cooperation projects and is currently supported by TEAP EU-CHINA project while developing the CAUA technological platform.

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