DynaGrow – Multi-Objective Optimization for Energy Cost-efficient Control of Supplemental Light in Greenhouses

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Abstract: The Danish greenhouse horticulture industry utilized 0.8 % of the total national electricity consumption in 2009 and it is estimated that 75 % of this is used for supplemental lighting. The increase in energy prices is a challenge for growers, and need to be addressed by utilizing supplemental light at low prices without compromising the growth and quality of the crop. Optimization of such multiple conflicting objectives requires advanced strategies that are currently not supported in existing greenhouse climate control systems. It is costly to incorporate advanced optimization functionality into existing systems as the software is not designed for such changes. The growers can not afford to buy new systems or new hardware to address the changing objectives. DynaGrow is build on top of existing climate computers to utilize existing infrastructure. The greenhouse climate control problem is characterized by non-linearity , stochasticity, non-convexity, high dimension of decision variables and an uncertain dynamic environment. Together, these mathematical properties are handled by applying a Multi-Objective Evolutionary Algorithm (MOEA) for discovering and exploiting critical trade-offs when optimizing the greenhouse climate. To formulate advanced objectives, DynaGrow integrates local climate data, electricity energy price forecasts and outdoor weather forecasts. In spring 2015, one greenhouse experiment was executed to evaluate the effects of DynaGrow. The experiment was run as three treatments in three identical greenhouse compartments. One treatment was controlled by a standard control system and the other three treatments were controlled by different DynaGrow configurations. A number of different plant species and batches were grown in the three treatments over a season. The results from DynaGrow treatment demonstrated that it was clearly possible to produce a number of different sales-ready plant species and at the same time optimize the utility of supplemental light at low electricity prices without compromising product quality.

1 INTRODUCTION

In 2009, Danish horticulture industry consumed 0.8 % of the total national electricity and 75 % of this consumed energy was estimated to come from supplemental light alone.

Several countries are at present time in a transition towards non-fossil renewable energy sources such as wind turbines. The large contribution of energy from renewable energy sources results in irregular electricity production, that leads to fluctuation in the electricity prices. An increased electricity price is a challenge for the horticulture industry that is positioned in a highly competitive market. A spot market electricity price structure has been introduced in the Scandinavian countries to provide an incentive for industry to utilize energy in cost effective hours where the supply of energy is plentiful (Nord Pool, 2016).

Existing fixed rate supplemental light control strategies are in contradiction to the flexible price structure. Fixed rate light-plans often consume energy at hours that are costly. The fixed rate strategies only plan according to the fixed time periods and do not take price structures into account. However, changing the light patterns may have severe effects on how the cultivar reacts. For example, negative effects could be bud dormancy, delayed leaf development, stem elongation, late seed germination and early flower initiation (Thomas and Vince-Prue, 1997). Hence, there is a need to optimize the utility of supplemental light to ensure that the light-plans represent the cheapest electricity prices and promote

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a high quality of the produced cultivar.

This paper proposes a system DynaGrow that integrates local climate data, electricity price and outdoor weather forecasts to formulate advanced control objectives. The core of the system is a customized Multi-Objective Evolutionary Algorithm (MOEA), that searches for coordinated Pareto-optimal light-plans that fulfil the specified climate control objectives. DynaGrow is a features-oriented software system divided into a number of features. Each feature encompasses an individual unit of software functionality and is implemented as loosely coupled plug-in modules. The feature-oriented separation of DynaGrow makes it relatively strait-forward to integrate to existing hardware devices and configure the system to optimize different objectives. Each set of objectives are strictly separated and can be configured to fulfill the specific climate control requirements given by the problem domain. Present time, DynaGrow supports two different climate control hardware platforms and support 37 different objectives (Sørensen et al., 2011).

Related work is shortly summarized in Section 2 Section 3 describes the different elements of DynaGrow and how they are connected. The most important control objectives optimized in the presented experiment, are formulated and detailed in Section 4. How the DynaGrow core is implemented as a genetic MOEA is described in Section 5. Section 6 describes the experiment that evaluate DynaGrow by growing three different cultivars based on three different climate control settings. The results of the experiment is described in Section 7. Next, the discussion reflects on how well DynaGrow optimized the identified objectives of the climate control problem. Last, Section 9 summarizes the article.

2 RELATED WORK

Research literature describes independent models that can contribute to an optimized greenhouse production and cut the energy consumption through development of intelligent control strategies. Aaslyng et. al created the foundation for a component-based climate control system IntelliGrow that optimizes the greenhouse climate (Aaslyng et al., 1996). The results showed that it was possible to reduce energy consumption by more than 20 %. Subsequently, there have been several projects in which the models and control strategies have been optimized (Aaslyng et al., 1999; Lund et al., 2006). The IntelliGrow concept is documented by Aaslyng et al. in (Aaslyng et al., 2005). Kjaer et al. developed the DynaLight system that provides a search-based approach to find the most cost-efficient use of supplemental light, based on a predefined setpoint of Daily Photosynthesis Integral (DPI), forecasted solar light and the spot-market electricity price (Kjaer and Ottosen, 2011; Kjaer et al., 2012; Clausen et al., 2012). The DynaLight algorithm is tightly integrated with the weather and electricity forecast services and does not support optimization multiple objectives.

None of the mentioned approaches support Pareto optimization of multiple independently developed objectives, to generate a coordinated set of setpoints that can be effectuated by the greenhouse climate control system. DynaGrow is the only approach that supports optimization of multiple objectives that are based on weather and electricity price forecasts.

3 DynaGrow

DynaGrow is designed to control climate-related growth factors by sensing and manipulating the greenhouse climate through the use of sensors and actuators. The physical setting of DynaGrow is a combination of a control machine, a number of connection domains and a controlled domain (Figure 1). The *control machine* consists of the DynaGrow software running on a PC, that is connected to a set of climate controllers. The climate controllers are connected to sensors and actuators (Connection Domains) that interact with the indoor climate of the greenhouse (Controlled Domain). A *connection domain* can act as a sensor or an actuator. Sensors provide measured input information m in form of input variables i to the *control machine*. Contrary, actuators influence the physical phenomenon c in the *controlled domain* according to output variables o provided by the machine.

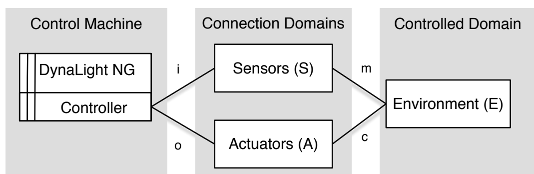


Figure 1: DynaGrow system overview.

The output of DynaGrow is determined by the system's *control objectives* that typically incorporates *models* of the physical environment. For example, a model of the photosynthesis process of a given plant in a greenhouse. Control objectives are formulated over a set of input variables i and output variables o, connecting the control machine with the connected domains. The control objectives are evaluated continuously in cycles by the machine, and is integrated into the *control process*. Each cycle is triggered at specific time intervals. For each control cycle, the system perceives the environment through its sensors variable *i*, optimizes the control objectives and changes the environment through its actuators to obtain the desired objective of the system. The result of a control cycle is a set of *output variables o* (*setpoints*) that are written to the actuators.

The control objectives are optimized using the CONTROLEUM-GA to guarantee a Pareto optimal trade-off between the multiple control objectives within computational tractable time (Ghoreishi et al., 2015). The CONTROLEUM-GA is a multi-objective genetic algorithm that incorporates domain specific variables and operators to solve dynamic optimization problems. The support for domain specific variables and operators, enable the algorithm to converge fast enough to optimize a larger number of objectives within each optimization cycle of DynaGrow.

4 OBJECTIVES

This section describes the most important objectives optimized in the DynaGrow experiment described in this article. Each control objective function can be formulated either as a minimization cost function or as a constraint. The objective function evaluates options proposed by the MOEA during the optimization process. The *option* argument is passed over by the MOEA and is a data-structure that contains a set of input variables *i* and output variables *o* that connects the *control machine* to the *connection domains*. In the pseudo-code, variables starting with an upper case letter represent information from the option provided by the MOEA. Lower case variables represent result variables used in the objective function.

```
SPARBAL(option)
1  lightPlanSum = CALCPARSUM(LightPlan, LampPAR)
2  balance =
       5 × ParDLI − (ParHist + ParFuture + lightPlanSum)
3  return balance
```

The PAR Light Sum Balance objective (SPARBAL) minimizes a Photosynthetically Active Radiation (PAR) sum balance, see Line 2. PAR designates the spectral wave band of solar radiation from 400 to 700 nanometers that photosynthetic organisms are able to utilize for photosynthesis. The *balance* is calculated over a five days time-window defined by current day, two days in the past and two days in the future. The PAR Integral Today and Past Two Days (*ParHist*) input is derived from historical data stored by DynaGrow. Data for the Expected Natural PAR Sum Remaining Day and Future Two days (*ParFuture*) input is provided by Conwx Intelligent Forecast Systems (Conwx, 2016). The PAR Day Light Integral (*ParDLI*) input specifies the average goal to be achieved over the five days period and is provided by the grower. The total light-plan PAR sum (*lightPlanSum*) variable is calculated based on the Installed Lamp PAR (*LampPAR*) input and the number of suggested light intervals in the *LightPlan* output. The *balance* is then calculated as the difference between the provided goal and the total of *ParHist*, *ParFuture* and the *lightPlanSum*. At the end of each day, the *ParHist* input will be updated with data from the past days. Similarly, the *ParFuture* input will be updated with data from next day. That is, the balance is calculated based on a five days sliding window.

```
SCHEAPLIGHT(option)
cost = ∑_{i=1}^{n} LightPlan.Switch_i × ElForecasts.Price_i ×
       (TotalLoad × LpTimeslot_i)
return cost
```

The Prefer Cheap Light objective (SCHEAPLIGHT) is specified as a cost function that minimizes the price of the Light-plan (*LightPlan*) based on El. Spot and Prognosis Prices (*ElCompPrices*). The electricity spot market price forecast is provided by Nord Pool and the longer three day prognosis is provided by Energi Danmark (Nord Pool, 2016; Energi Danmark, 2016). The Total Lamp Load (*TotalLoad*) is calculated as the Installed Lamp Effect (*InstLampEffect*) multiplied by the Greenhouse Size (*GreenhouseSize*). The index *i* is the time-slot index of the *LightPlan*. For each light time-slot *i*, the sub-cost is calculated as the Total Lamp Load (*TotalLoad*) multiplied by the light-plan time-slot interval T_i and the electricity price $ElForecasts.Price_i$. The total cost of the Light-plan (*LightPlan*) is then the sum of all the sub-costs for each of the light intervals ($LightPlan.Switch_i$). The $LightPlan.Switch_i$ is zero for light switched off and one for when the supplemental light is lit.

5 IMPLEMENTATION

The CONTROLEUM-GA function shows the pseudo-code for the genetic algorithm implementation used by the core of DynaGrow. Note that the line numbers break and continue in places where sub-functions are called from CONTROLEUM-GA ().

```
CONTROLEUM-GA(time, oldPop)
1  if oldPop.isNotEmpty
2      for each oldSolution ∈ oldPop
3          ADD-NONDOMSOLUTION(
                       COPY(time, solution))
4  for i = 0 to POPSIZE
5      ADD-NONDOMSOLUTION(D-INIT(time))
17 while isNotTerminated
18     for i = 0 to i ≤ POPSIZE
19         if RANDOM-DOUBLE() < MUTATIONRATE
20             child = S-MUTATE(RANDOM(pop))
27         else
28             child = S-CROSSOVER(RANDOM(pop),
                                   RANDOM(pop))
34         ADD-NONDOMSOLUTION(child)
```

The CONTROLEUM-GA function has two arguments: 1) a time-stamp *time* for when the algorithm is executed, and 2) the population *oldPop* from previous executions. The time-stamp *time* is used for dynamic optimization problems that use the start time of the optimization. The algorithm is separated into the following phases: Initialization, Ranking, Mutation, Crossover and Termination.

Initialization: A population consist of a number of non-dominated Pareto optimal solutions. Each solution is represented by a data-structure that has a collection of objective results $solution.objectives$ and decision variables $solution.variables$. A solution can have multiple different types of domain specific variables; e.g., temperature, CO_2 and light-plan. In this work we focus on the light-plan variable. Line 1 checks if the previous population *oldPop* is empty. The population *oldPop* is empty the first time the algorithm is executed. If the population *oldPop* exists from previous executions, it is copied into the new non-dominated population *pop* (Line 3). A domain specific initialization operator D-INIT is implemented for each type of decision variable (Line 5). For example, the supplemental light-plan is initialized by the domain specific initialization operator that is an implementation of the D-INIT function. For example the different time resolutions of light-plans are encoded in the light-plan variable.

CONTROLEUM-GA Line 17 test if the evolution should terminate. Evolution is terminated after a specified time limit, after a number of generations or when the population is stable.

Ranking: The function ADD-NONDOMSOLUTION sorts all solutions in the population *pop* according to the Pareto dominance relation (Line 8). That is, the objectives are ranked given the proposed decision variables $solution.variables$. The results of the evaluations are assigned to the objective values $solution.objectives$ for each proposed solution. Only non-dominated solutions are added to the population *pop*.

```
ADD-NONDOMSOLUTION(newSolutionA)
6  for each oldSolutionB ∈ pop
7      flag =
8        PARETO-COMPARE(newSolutionA, oldSolutionB)
9      if flag == ADOMINATESB
10         REMOVE(oldSolutionB, pop)
11     elseif flag == BDOMINATESA
12         return false
13     elseif DISTANCE(newSolutionA, oldSolutionB) < EPS
14         return false
15 ADD(newSolutionA, pop)
16 return true
```

The function PARETO-COMPARE compares if a solution *newSolutionA* dominates a solution *oldSolutionB* or visa verse. If solution *newSolutionA* dominates solution *oldSolutionB* then solution *oldSolutionB* is removed from the population *pop* (Line 10). Contrary, if solution *oldSolutionB* dominates solution *newSolutionA* then it is not added to the population *pop* (Line 12). Two solutions are defined as the same, if the Euclidean DISTANCE between two solutions in the objective space, is less than the level of significance defined by constant EPS. In case *newSolutionA* is the same as *oldSolutionB* then it is not added to the population *pop* (Line 14).

Mutation: For each generation, solutions are randomly selected a number of times for mutation. The number of mutations is determined by the constants MUTATIONRATE and POPSIZE. For example, if POPSIZE is 100 and MUTATIONRATE is 50 % then 50 randomly selected solutions are mutated. If a mutation results in a non-dominated solution then it is added to the population *pop*.

```
S-MUTATE(solution)
21 i = RANDOM-INT()
22 solution.variables[i] = D-MUTATE(solution.variables[i])
```

Mutation is applied at solution level and domain variable level. At solution level a random decision variable is selected for mutation in Line 21 using a generic uniform mutation (UM) operator. Each decision variable has its own domain specific mutation operator D-MUTATE. The D-MUTATE operator is applied on the randomly selected variable in Line 22. D-MUTATE-LIGHT shows the implementation of D-MUTATE for a light plan variable. The selected light plan variable is copied and a randomly selected index in the plan is negated. That is, if the light state for the selected index was ON, then after mutation it will be set to OFF.

```
D-MUTATE-LIGHT(lightPlan)
23  lp = COPY(lightPlan, TIMEINTERVAL)
24  i = RANDOM-INT(lp.size)
25  lp[i] = ¬lp[i]
26  return lp
```

Implementations of D-MUTATION operators incorporate domain knowledge to ensure that the values of the decision variables are always viable. In case of the light plan variable, the D-MUTATION-LIGHT incorporate knowledge about time-resolution and which index of the light plan that is viable for change (Line 23 and 24). For example, if a light interval only can change once for a given period of time, or if a light state is always fixed, then it is implemented in the implementation of the D-MUTATE function for the given variable. Each domain mutation operator defines a range for a specific type of decision variable (temperature, energy, CO_2, etc.). The intersection of these ranges defines the viability space of the decision variable.

Crossover: Solutions are randomly selected for crossover for a number of iterations. The number of crossover iterations is determined by the constant POPSIZE. Crossover is applied at solution and decision variable level. The solution level crossover function S-CROSSOVER is called in CONTROLEUM-GA Line 28.

```
S-CROSSOVER(solutionA, solutionB)
29  i = RANDOM-INT(solutionA.variables.size)
30  solutionA.variables[i] =
      D-CROSSOVER(solutionA.variables[i],
                  solutionB.variables[i])
31  for j = i+1 to j < solutionA.variables.size − 1
32      solutionA.variables[j] = solutionB.variables[j]
33  return solutionA
```

Random variables from two solutions *solutionA* and *solutionB* are selected for crossover at decision variable level using a generic one-point crossover operator (Line 29,30). At the other variables from the selected index $i+1$ till last index from *solutionB* is copied to *solutionA*.

The domain specific D-CROSSOVER operator is applied on the selected decision variables in Line 30. The D-CROSSOVER function is the domain specific crossover operator for two light plans *lightPlanA* and *lightPlanB*. In the DynaGrow experiment, the two light plans are crossed by a standard one-point crossover operator but more complex outputs requires more knowledge encoded into the output datastructure.

6 EXPERIMENT

In February 2015 a greenhouse experiment was executed to evaluate the cost effectiveness and the qualities of the DynaGrow software. The experiment was executed as three treatments in three identical greenhouse compartments. The first treatment (S SON-T) was executed by a standard control system with SON-T lamps and fixed day length of 18 hours. The second treatment (DG SON-T) was equipped with SON-T lamps but controlled by DynaGrow. The third treatment (DG LED) was equipped with LED lamps and was controlled by DynaGrow. For both the DynaGrow compartments the control cycle was set to 5 minutes.

The PAR Day Light Integral provided by natural light was on average approximately 12 $mol\ m^{-2}\ d^{-1}$ and the DLI goal for all of the evaluated control strategies was set to 8 $mol\ m^{-2}\ d^{-1}$.

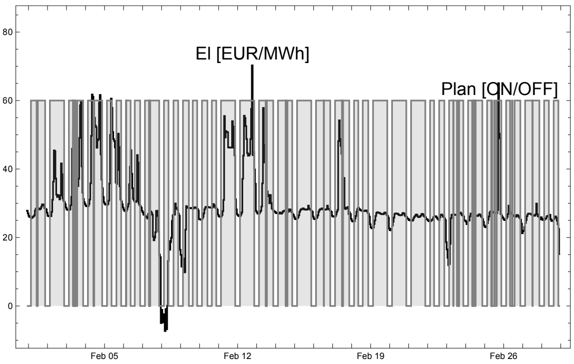
The cost of the energy, used for supplemental light, was calculated based on when the light was lit and the price of electricity for that specific time. The electricity prices was for the west part of the Danish electricity grid (DK1). Each compartment is 76 m^2 and in the SON-T compartments there is 16 lamps installed. A SON-T lamp has an effect of 600 Watt. That is, the installed effect for the SON-T compartments is $(16 \times 600\ W)/76\ m^2 = 126\ W/m^2$. In comparison, a LED lamp has an effect of 190 W and the LED compartment has 38 LED lamps installed. The total installed effect for the LED compartment is then $(38 \times 190\ W)/76\ m^2 = 95\ W/m^2$.

The granularity of the SON-T light-plans was set to one hour due the physical properties of the lamps. A SON-T lamp can not tolerate to be switched ON/OFF to often due to heating. The granularity of the LED light-plans was set to 15 minutes as LED lamps tolerate to be lit in short intervals.

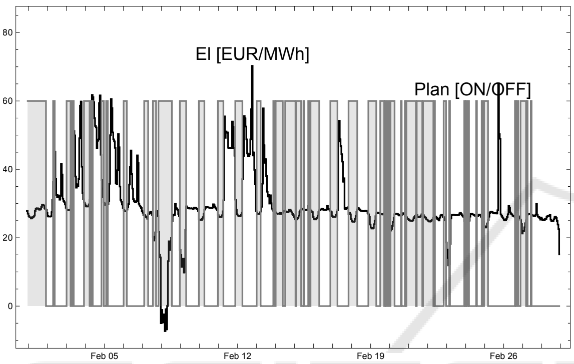
Roses, Kalanchoe and Chili batches were grown in the three treatments over the season, to evaluate the effect of the different light-plans. The cultivars were harvested a maturation, meaning that plants from the different treatments were sometimes harvested at different times.

7 RESULTS

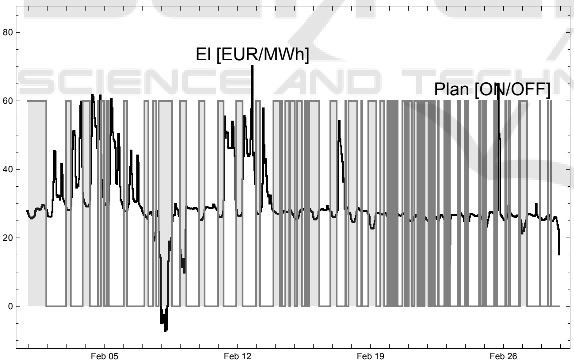
Figure 2 illustrates the light-plans, effectuated for each of the compartments, together with the electricity prices provided from the Nord Pool power spot market (Nord Pool, 2016). The light-plan for the S SON-T compartment has fixed rates as expected from the standard fixed rate light control strategy.



(a) Standard SON-T



(b) DynaGrow SON-T



(c) DynaGrow LED

Figure 2: Comparison of light-plans optimized by different strategies in February 2015.

Figure 2a shows that the fixed rate light-plan clearly requires supplemental light at hours where the electricity price is high.

In contrast, the DG SON-T light-plan is quite different to the S SON-T light plan. Figure 2b illustrates the DG SON-T light-plan for the same experiment period. The DG SON-T light-plan has the same one hour granularity as the S SON-T light-plan but expensive supplemental light hours are avoided. That is, the CONTROLEUM-GA has clearly optimized the SCHEAPLIGHT objective in order to generate the DG SON-T light-plan.

The DG LED light-plan is similar to the DG SON-T light-plan as both light-plans are optimized by same MOEA with same objectives, see Figure 2c. The differences between the DG SON-T and DG LED light-plans are the granularity of the generated light-plans and the energy consumed by the different type of lamps. The finer granularity (15 minutes) of the DG LED light-plans can be observed February 20-23 in Figure 2c.

Table 1: Energy results of the experiment February 2015.

Control	Energy [KWh]	Energy [%]	Cost [€]	Cost [%]
S SON-T	4139.2	100	127.0	100
DG SON-T	2482.6	40	62.4	51
DG LED	1828.5	56	45.3	64

Table 1 provides a summary of the experimental energy results for February 2015. The total energy consumed by the S SON-T treatment (control) was 4139.2 KWh and was set as the reference. The DG SON-T the DG LED treatments consumed 40 % and 56 % less energy compared to the reference, respectively. Furthermore, the total cost of S SON-T light-plan (reference) was 127 €. The DG SON-T and LED treatments was 51 % and 64 % cheaper than the reference, respectively.

Table 2: Light hours and DLIs of the experiment February 2015.

Control	Average DLI [mol $m^{-2}\,d^{-1}$]	DLI [%]	Suppl. Light hours [h]	Suppl. Light [%]
S SON-T	8.5	100	432.3	100
DG SON-T	6.5	19	259.3	40
DG LED	6.5	19	253.3	41

Table 2 shows the experimental DLI results for the three compartments in February 2015. For the reference S SON-T treatment, supplemental light was lit in 432.3 hours. In comparison, supplemental light was lit for 259.3 and 253.3 for the DG SON-T and DG LED treatments, respectively. That is, the DG SON-T and DG LED treatments had respectively 40 % and 41 % less supplemental light hours than the reference. The DLI goal for each treatment was 8 $mol\ m^{-2}\ d^{-1}$. Additionally, the average DLI for the S SON-T treatment was higher than the DG SON-T and DG LED treatments. The two DynaGrow treatments obtained the same average DLI of 6.5 $mol\ m^{-2}\ d^{-1}$ which is 19 % lower than the reference and 1.5 $mol\ m^{-2}\ d^{-1}$ lower than the DLI goal.

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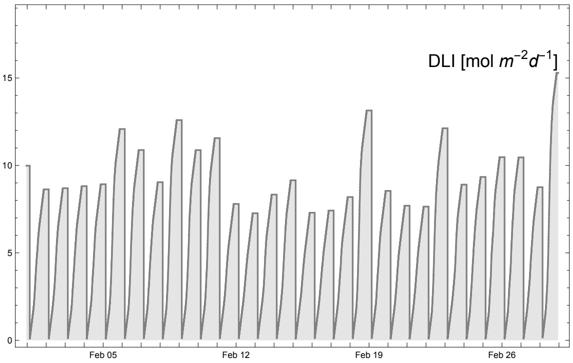
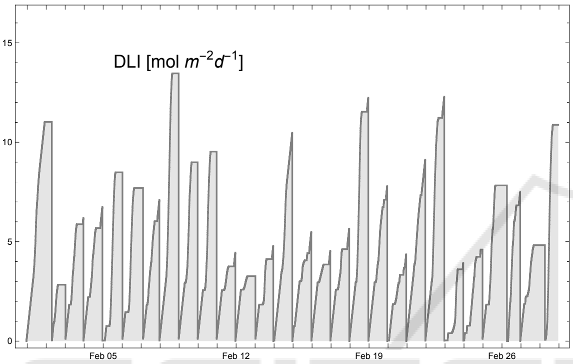


(a) S SON-T



(b) DG SON-T and "DG LED"

Figure 3: PAR light sum comparison from tree experimental compartments optimized by different strategies in February 2015.

Figure 3 shows the accumulated DLIs for each of the treatments. The DG SON-T and DG LED DLIs are similar but the S SON-T DLIs are in average higher which corresponds to the results in Table 2.

The properties of the cultivars was reported for Roses, Kalanchoe and Chili by measuring the relative growth rate (RGR), relative dry weight (RDW) and the number of flowers. In general the results are reflecting that plant growth was related to the climate conditions of the treatments with species and genotype-specific differences. All the plants grew well in the three climates and reached maturation within acceptable time. Figure 4 is pictures of Kalanchoe (Simone) grown under the S SON-T (left), DG SON-T (Middle) and DG LED (Right) treatments. Further details about the results of growing the different cultivars in irregular light conditions can be found in work by Ottosen et al (Kjaer et al., 2012; Kjaer and Ottosen, 2011; Kjaer et al., 2011). Last, is was concluded that all the grown cultivars was in a sales-ready quality.

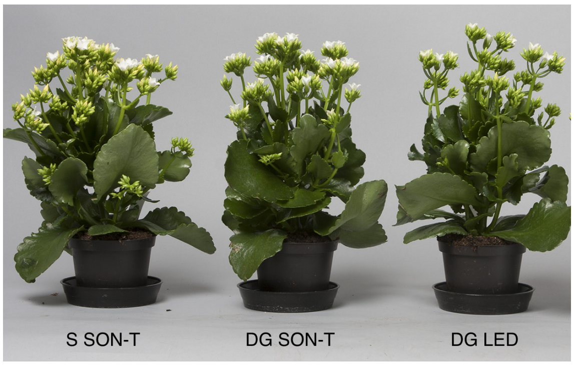


Figure 4: Kalanchoe (Simone) as a result of the S SON-T (left), DG SON-T (Middle) and DG LED (Right) treatments.

8 DISCUSSION

The DG SON-T and LED treatments was 51 % and 64 % cheaper than the reference, respectively (Table 1). In euro, that is a saving of 81.7 € per month in the best case for a compartment of 76 m^2. In Denmark, some industrial growers have greenhouse facilities that is more than 65000 m^2 and the documented energy saving can have a huge potential economical impact. It's important to emphasise that the price calculation does not include rates for Public Service Obligations (PSO), but is based purely on the spot market prices and the theoretical installed effect in each compartment.

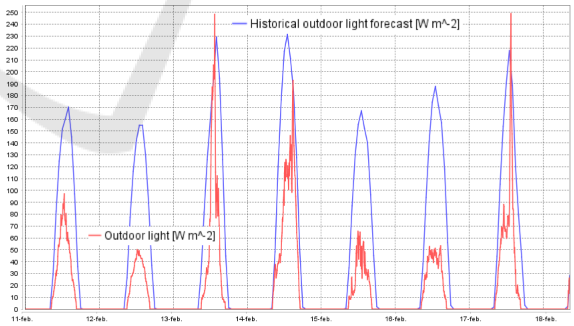


Figure 5: Optimistic outdoor light forecast (bell curve) and the actual outdoor light data for February 11-18.

The lower DG SON-T and DG LED DLIs was not expected as similar effect (light intensity) should have been installed in the S SON-T treatment. The equal DG SON-T and DG LED DLIs indicate that the optimization of PAR Light Sum Balance objective has been achieved but with a too low goal. A reason for the lower DLI can be explained by the natural light forecast provided by the external service. The cost calculation in the SPARBAL objective de-

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pends on a precise outdoor light forecast, see SPARBAL Section 3.

Figure 5 illustrates the time-series of the outdoor light forecast and the actual outdoor light. The time-series reveal that the outdoor light forecast has a tendency to be too optimistic. An optimistic light forecast will influence the sliding window balance in the SPARBAL objective as the *ParFuture* will promise more light than is the actual light. If the *ParFuture* is optimistic over several days, like illustrated in the time-series in Figure 5 (February 11-18), then the average of the *ParDLI* will never be achieved within the sliding window. That is, the result will be a lower average DLI as indicated by Table 2.

9 CONCLUSION

The increasing energy prices is a challenge for growers and need to be addressed by utilizing supplemental light when electricity prices are low and without compromising the growth and quality of the crop. Optimization of such multiple conflicting objectives requires advanced strategies that are currently not supported in existing greenhouse climate control systems.

The result of the winter experiment 2015 demonstrates that DynaGrow utilizes supplemental light at low electricity prices without compromising the growth and quality of the crop compared to standard fixed rate supplemental light control. It was possible to produce a number of different cultivars where the supplemental light (SON-T or LED), the temperature and CO_2 was controlled by the DynaGrow software. The energy savings are achieved in relation to a control treatment with a fixed day length, but only if the DLI is comparable between the treatments.

In Denmark, DynaGrow will have a high impact on cost in the beginning and end of the growing season, when there is a huge potential for optimizing the supplemental light.

There is an unexplored potential to optimize the utilization of supplemental light, temperature, CO_2, humidity and other climate variables simultaneously by formulating multiple advanced control objectives based on models already available from the extensive horticultural literature.

The results clearly demonstrate, that DynaGrow supports a dynamic climate control strategy by optimizing multiple control objectives that results in a cost-effective control of the greenhouse climate.

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