

Review

Model Predictive Control of Smart Greenhouses as the Path towards Near Zero Energy Consumption

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Received: 2 June 2020; Accepted: 11 July 2020; Published: 15 July 2020



Abstract: Modern agriculture represents an economic sector that can mainly benefit from technology innovation according to the principles suggested by Industry 4.0 for smart farming systems. Greenhouse industry is significantly becoming more and more technological and automatized to improve the quality and efficiency of crop production. Smart greenhouses are equipped with forefront IoT- and ICT-based monitoring and control systems. New remote sensors, devices, networking communication, and control strategies can make available real-time information about crop health, soil, temperature, humidity, and other indoor parameters. Energy efficiency plays a key role in this context, as a fundamental path towards sustainability of the production. This paper is a review of the precision and sustainable agriculture approaches focusing on the current advance technological solution to monitor, track, and control greenhouse systems to enhance production in a more sustainable way. Thus, we compared and analyzed traditional versus model predictive control methods with the aim to enhance indoor microclimate condition management under an energy-saving approach. We also reviewed applications of sustainable approaches to reach nearly zero energy consumption, while achieving nearly zero water and pesticide use.

Keywords: model predictive control; precision agriculture; greenhouse; control strategies; energy saving; sustainability

1. Introduction

Agriculture plays a key factor in ensuring food security, stability, and strengthening the economy of countries. It has to fulfil a growing number of regulations on environment and quality. The integration of new technologies in the agro-alimentary sector may help meet these challenges [1]. Sustainable food and energy provisions are a key concern globally [2]. Greenhouse farming, as a sustainable intense food-production system, may contribute to feeding the world [3]. Encouraging the intensive use of greenhouses in agriculture may help cope with the barriers facing the shift towards precision and sustainable agriculture. A sustainable smart approach might support preserve energy and water resources, mitigating environment impacts, enhancing quality of life, producing local socio-economic and environmental benefits, and minimizing the effects of climate changes [4]. The main objective of a greenhouse is to ensure an optimum environment for crop cultivation [5].

Precision agriculture market sizes to expect 15% gains to 2025, says a 2019 GMI report. The precision agriculture market revenue is estimated to surpass a valuation of USD 12 billion by 2025 [6]. The market increase is due to the growing implementation of smart agricultural practices. Advances in control algorithms, big data, information and communication technologies, and integration of renewable energy systems constitute the other factors contributing to the smart agriculture market growth. Moreover, it is stated that the managed precision agriculture services segment is projected to reveal a

progress rate of over 27% from 2019 to 2025 [6]. Canada, US, Germany, Japan, China, Middle East, and South America constitute the emerging markets for smart greenhouses.

Given population expansion, climate changes, shortage in water, and energy resources, traditional cultivation is facing many challenges in meeting the increasing food demands. Accordingly, crop development in greenhouses can be taken into account as a practical solution to meet environmental regulations, energy and water saving options, and meet population demands in a sustainable way. A greenhouse is an enclosure that keep climate variables, like humidity, air mass, temperature, and others in preferred intervals to stimulate crop development. Thus, its main objective is the regulation of climate environments considering the plant life cycle and ensuring production during all seasons [7]. A smart greenhouse, however, may be taken into account as a new active actor in the agriculture sector, which might contribute to the fast conversion to sustainable and precision agriculture and modernization of the sector by taking advantage of advanced control techniques, metering and communication infrastructures, and smart management solutions. Each greenhouse has heating, ventilation, and air conditioning unit, pumps, fans, CO₂ generator, artificial lighting, sensors, management unit, and information and communication infrastructure.

The aim of this paper is two-fold. First, it presents a literature review addressing the current technological and methodological models and methods to create, monitor, and control the interior greenhouse microclimate condition, defining the optimal environment for crop development as well as controlling the complex interaction among dependent variables. Secondly, specific interest will be dedicated to recent innovative strategies to improve the effectiveness of resource use in the energy management of the greenhouse considering the possibility to obtain a solution that guarantees zero energy/water consumption and zero waste production—in a few words, how to make greenhouse crop production sustainable.

In this work, Scholar Google database has been used as a data source for the bibliographic analysis. The literature review is concentrated for the period of 2005–2020, but 31% of the citations are dated 2020, 60% concerns papers published in the period of 2016–2020, and only 14% are papers prior to 2010.

The MPC application in the context of greenhouse climate control is a topic of huge interest, but the related literature is still limited. Using keyword search “model predictive control MPC greenhouse climate control”, about 3,500 results in Scholar Google appear for the period of 2015–2020, with a significant boost in respect to the previous period of 2000–2015, which provided only 2,200 results, for the same keywords. Figure 1 displays the number of publications, per year, with regard to this bibliographic search by Scholar Google for the last two decades.

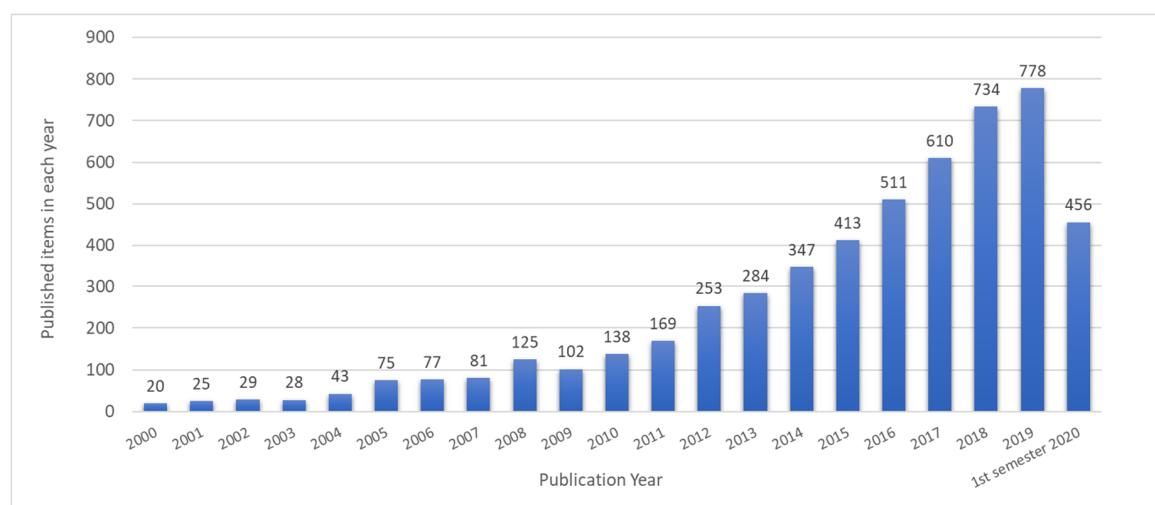


Figure 1. Number of publications concerning model predictive control applications in greenhouse climate control field (Source: Scholar Google).

Other similar themes related to MPC applications in building climate control (about 16,700 results in Scholar Google for the interval of 2015–2020), artificial neural networks application in agricultural engineering [8] or, in general, the computational intelligence methods applied to renewable energy source optimization received in the last decade, have received increased attention [9]. Despite those trends, there is a lack of literature dedicated to the comparison of MPC applications with other traditional control models in the greenhouse control climate framework.

1.1. Technologic Aspects of Modern Greenhouses to Enhance Energy Management

In Europe, in traditional greenhouse, thermal heating demand represents about 80% of the energy consumption, while electric energy represents about 15% [10]. To save energy, it is necessary to turn the management of the greenhouse towards a new smart approach, taking into account technological and methodological features. The introduction of renewable energy sources can evidently contribute to energy saving [11].

A greenhouse is a protected environment realized with metallic frames, which support transparent materials. Modern greenhouses are designed with special attention being paid to the shape, dimension, orientation, and innovative materials they are made of. In the literature, the importance of a suitable design and correct orientation of a greenhouse structure according to the location and to external climates has been demonstrated [12–15]. The authors of [16,17] have presented exhaustive reviews in this field.

Light represents a key factor for plant development. The greenhouse is protected against weather climate variations (solar irradiation, rain, wind, . . . etc.) by a cover material that must satisfy several standards and criteria. During the day, plants absorb a fraction of sunlight through the cover material, while, the rest is reflected. Few studies have investigated the benefits obtained by the use of polyethylene and single or doubles layers glass panels in existing greenhouse covers in order to reduce condensation and heat losses [18]. New smart glazing technologies may be active or passive according to their ability to change optical characteristics [19]. Greenhouse producers and farmers are also keenly looking for the best solutions to increase the transmission of radiation through the cladding or shading covers [20]. In [21], the authors evaluated the effect of different shading types on solar and thermal radiation in a greenhouse. The main aim of the shading adoption is the possibility to reduce the quantity of solar energy that filters into the greenhouse during the summer months, thus reducing water consumption for crop irrigation [22,23]. Infrared filters realized by plastic or glass films have been successfully used to guarantee photosynthetically active radiation (PAR) transmission, at the same time preventing pests. The use of plastic screens in greenhouse vents may also prevent the access of certain species of insect pests [24]. Specific requirements of porosity and geometric parameters of insect-proof screens have to be considered [25].

At night, greenhouses use artificial lighting to extend the development cycle of the crops. The adoption of artificial light is a critical issue in order to fit the current demand for irradiance specific for each crop growth, especially in the winter season. The greenhouse lighting technique is carried out with two distinct objectives: alter the natural photoperiod and stimulate the photosynthetic process. Photoperiodism refers to the phenomenon that allows plants to measure the period of light and dark during the day. Photosynthesis is not only influenced by light intensity but also by external factors, such as availability of water, concentration of CO₂, and temperature. Other internal factors are related to pigment content, leaf structure, and genetic characteristics of the plants. When internal and external factors are in equilibrium, in periods of low sunlight irradiance, light irradiation will be very effective. Before LED lamps were introduced to the market, artificial lighting was generated by high-pressure sodium (HPS) lamps, which have a limited duration, high energy consumption, and produce high heat that made it impossible for them to be placed near plants. With the arrival of LED lighting, and their subsequent application in greenhouses, the wavelengths of the lights useful for plant growth can be manipulated, generating blue (B, 400–500 nm) or red (R, 600–700 nm) or far-red (FR, 700–800 nm) [26]. Besides, in [27], the authors observed that, by the application of a parallel particle swarm algorithm,

using optimal location of an LED array, significant energy saving is obtained with respect to either the tradition fluorescent lamps (saving 82.6%) or incandescent lamps (saving 54.2%).

Furthermore, crops need CO₂ for the photosynthesis process; consequently, a CO₂ generator is needed to stabilize the dynamic rates according to specific needs. Moreover, a set of local pumps are available to fulfil the requirement with certain precision of fertilizers and water requirements.

Heating/cooling and ventilation technologies are used to manipulate the thermal load, humidity, and air mass circulation. The heat needed in the greenhouse may be generated by active or passive systems [28]. The active system consists of a boiler, electric heaters, or combustion chamber able to convert different type of fuels to heat energy [29]. The heating system currently produces steam or hot water, which is pumped in the greenhouse by a network of tubes. The heat distribution phase by water may be realized in different ways: by pipe heating, which may be integrated into the floor of the greenhouse or along the perimeter or hoisted [30], or under the benches at the crop level for soil warming [31]. The steam system is usually located near the greenhouse roof to decrease condensation; while the radiant heater releases heat to the floor level towards the surrounding air. Finally, infrared radiant heater consists of low intensity infrared radiators [32]. The passive system is independent of artificial fuels, but based on solar energy [33]. Recently, several research works have studied heating systems using RES (renewable energy resources), where solar energy represents the most important resource in terms of sustainability [34]. Solar active systems consist of a set of different collectors, while passive systems are implemented by taking into account the fact that the greenhouse structure may acquire and accumulate solar energy [35]. In the active system, in order to collect heat in the solar periods and store energy for the winter seasons, electricity for heating and greenhouse management in general may be produced using PV (Photovoltaic) panels on the roof of the greenhouse. Different approaches have been studied to integrate solar-based energy systems with new innovative PV technologies. The most popular inorganic modules include mono and poli-crystalline silicon [36], thin film solar cell technology [37], or PVs based on organic materials, which focus on the conductive properties of materials as polymeric membranes to absorb different wavelengths of light [38] or, more recently, dye sensitized solar cells (DSSCs) [39]. The silicon photovoltaic panels have a power efficiency of about 17% and a long lifetime. Thin films have both lower efficiency and manufacturing costs, while organic panels have lower efficiency but strong flexibility and ability to be customized in the design [40].

In order to obtain the correct temperature and humidity for plants, a greenhouse has to be equipped with proper ventilation and cooling systems [41]. The cooling systems operate by generating heating loss when the external temperature exceeds that of the internal. This may be realized by greenhouse fans, passive or active ventilation shutters, or evaporative cooling systems. Besides, during peak conditions, it would be necessary to control internal temperature and humidity levels by air handling units (AHU), which work for both heating and cooling design [42,43]. Recently, the use of direct evaporative cooling systems, based on the recirculation of a part of the cooled air, has been successfully tested as an alternative to conventional systems, above all, in locations with very hot and dry weather conditions [44]. In terms of sustainable resources, ground and groundwater heat pumps (GHPs) merit growing interest in civil and greenhouse applications [45,46]. They exploit the property of the ground or the water to ensure constant temperature at proper depth [47]. Usually, GHPs may be realized by boreholes or energy piles. The former consists of pipes that are buried in the ground, by ground-loop vertical or horizontal methods, in order to induce an exchange of heat with the soil [47–50]. Different forms and diameter for pipes have been tested to compare GHPs' performances. In [51], the authors demonstrated that the use of elliptical U-tubes decreases the thermal resistance by 17%, in respect to traditional tubes, and improves the coefficient of performance (COP) of Ground-Coupled Heat Pumps (GCHPs) systems. The GHP based on energy piles, more suitable for building, offer the advantages of a more consistent thermal storage capacity [52]. The GHP systems may be open or closed if the heat fluid circulated within the open or closed network of pipes is located under the ground. These systems have high installation and infrastructural costs but offer higher

performance in respect to traditional heating/cooling systems [53]. The internal parameters of the greenhouse are related to each other and globally influence decisions on the amount of water to be supplied to the plants. The quantity of water to be used in the irrigation process affects not only the quality of the crop and their development, but also the maintenance costs and pest uses. The main parameters to be checked in irrigation control are related to soil moisture, relative humidity, soil and air temperature, radiation, and salinity in the water; and soil and crop evapotranspiration (ETC) [54]. The irrigation use efficiency (IUE) and water use efficiency (WUE) are subjected to economic gain obtained by the greenhouse production and to water consumption. An efficient use of water depends on reshaping the crop distribution according to the climate condition selecting control strategies to reduce water waste [55].

1.2. Requirement of Tracking Indoor Variables to Enhance Production in Greenhouses

The definition of the architecture used to track physical variables to enhance crop growth is a crucial issue in managing proper greenhouse indoor conditions specific for each cultivation. In traditional agriculture, manual management of the environmental condition is achieved with physical and economical efforts by the farmers. Recently, the introduction of ICT (information and communication technologies) and intelligent network management systems has produced a significant increase in efficiency and effectiveness of the greenhouse exploitation. The development of software and hardware systems represent the main task in order to apply smart technology in greenhouses. In the literature, the current smart management greenhouse systems may be described as consisting of three main integrated subsystems: the monitoring sensor node network system, the communication network, and the control unit.

The monitoring network consists of several nodes that are usually connected by wireless sensor networks (WSN) technology [56–58] and placed in the different zones of the greenhouse in order to identify changes in key variables [59]. Each node works in a distributed way and consists of different sensors, each monitoring specific environmental parameters. Two types of sensors may be considered. First, bio-chemical sensors monitor data related to the crops, plants, soil, or other micro-organisms in order to identify the presence of pesticides or chemical elements. Secondly, physical sensors are adopted to monitor air temperature and humidity, pressure, and irradiation data [60]. The data may be recorded in real time, with predefined time intervals, in each node of the network. They are usually saved in a local datalogger and transmitted to the electronic control unit (ECU) by wireless communication, according to common wireless standards as Zigbee or WiFi [61]. From a software viewpoint, Arduino and Raspberry Pi are the technologies that have received the most attention in the implementation of ECU [62]. A review on recent results in energy efficiency in greenhouse applications may be found in [63].

2. Review of Methods and Applications

2.1. Traditional PID/relay Control Methods

The most advanced traditional controller used in greenhouse management refers to proportional, integral, and derivative (PID) controllers. The general formalization of a PID controller is as per the following:

$$u(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \frac{de(t)}{dt} \quad (1)$$

where $u(t)$ is the control, $e(t)$ is the error of the signal, and K_p , K_i and K_d are the proportional, integral, and derivative constants, respectively. The main difficult task is to identify the three constants that affect the controller performances in order to minimize errors between a desired set point and the measured control variable $u(t)$. This identification process can become very hard in Multiple Input Multiple Output (MIMO) systems, where multiple controls and multiple state variables to be controlled are present. In fact, the greenhouse represents a very complex system and the dynamics of the processes

are correlated to several state variables, such as temperature and humidity. The most frequently used control is the simple on/off. This control model is a simple relay switching on/off the actuators when the controller output is below or over the set points, as adjusted by a proper hysteresis to avoid switching on/off too frequently. Many innovative approaches in literature are implemented to control internal microclimate by fuzzy PID [64], adaptive PID [65,66], or tuning PID parameters by Evolutionary Algorithm (EA) [67] or by Neural Network (NN) [68]. The artificial NNs (ANNs), in particular, are referred to computing systems and machine learning models based on the biological structure of the brain neural network. Those techniques are largely used in the literature in the greenhouse microclimate context [69] such as to determine the indoor temperature and humidity [70], to predict inside climatic conditions [71] or to forecast energy consumption [72]. In [73], the authors review the applications of ANN in greenhouse technology.

Despite the large use of PID control and evolutionary methods to improve the quality of the performances, this approach needs computational efforts to tune the gain parameters and it often lacks in efficiency when the system presents non linearities and strong disturbances, especially in real time control applications [74]. In addition, relay and PID controls fall in the category of reactive controllers, which do not take into account the future evolution of the systems. For example, if the temperature is below a given threshold, a reactive controller can promptly provide energy to make the temperature warmer, despite the external temperature increasing or not. Taking into account the future evolution of the system, control strategies should aim to avoid useless energy consumption.

Thus, more flexible methods have to be implemented in order to adapt the control strategies to the dynamics of the greenhouse systems, which may be based on the forecast of trends of main significant state variables by a specific, although simplified, model.

2.2. Model Predictive Control Definition and Examples in the Energy Sector

The model predictive control (MPC) approach is used to design a series of control methods, which require the minimizing of an object function subject to constraints in a specified time horizon. There are different types of models depending on the cost function. They may be nonlinear, linear, robust, stochastics and with cooperative or non-cooperative approaches [75]. Figure 2 shows a graphical representation of an MPC.

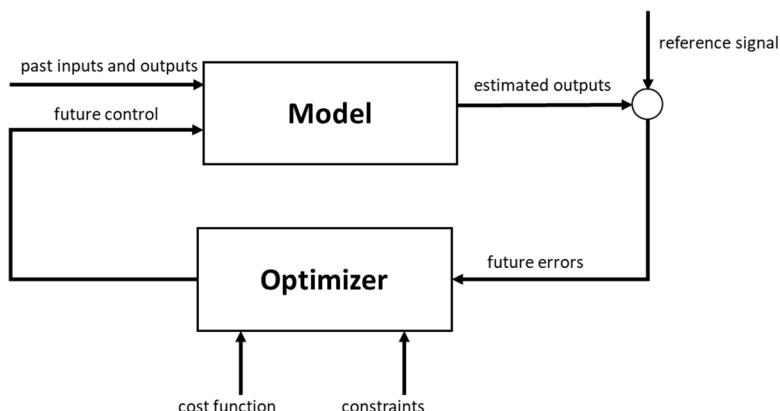


Figure 2. MPC design.

In the MPC approach, the main issue is to define future variable values at the current time instant using prediction by a specific model. In fact, at each time instant, the time horizon is computed on a rolling time windows starting in that specific instant and lasting for a fixed duration. In the optimization results, only the first values of the optimal control are taken into account. As an example,

in discrete time, on one rolling horizon window, a typical problem can be written using the following mathematical formulation:

$$\min_u \frac{1}{2} \sum_{k=0}^{N-1} [x'(k)Qx(k) + u'(k)Ru(k)] + x'(N)Px(N) \quad (2)$$

$$x(k+1) = f(x(k), u(k)) \quad k = 0 \dots N-1 \quad (3)$$

$$u_{min} \leq u_k \leq u_{max} \quad k = 0 \dots N-1 \quad (4)$$

where

- Equation (2) is the cost function expressed as a quadratic function, i.e., the variables represent the deviation from a reference value that is taken into account as 0
- Equation (3) is the function representing the future dynamic behavior of the system according to a specific theoretical model
- Equation (4) represents thresholds limiting the control

and where

- $x(k)$ is a vector of state variables at instant k
- $u(k)$ is a vector of control variables at instant k
- Q, P are semi-definite positive representing the cost of the state
- R is definite positive representing the cost of the control.

It is important to observe that this problem is solved at each time step on the respective rolling time horizon. Thus, its solution should be found in reasonable time, that is less than the duration of a sample time. It is also important to observe that just $u(1)$ is applied, offering more robustness of the solution to the possible imprecision of the forecasting model.

Issues with the MPC include stability, feasibility, and computations that depend on the choice of the model. A suite model for the MPC problem consists of obtaining a good tradeoff between the computational complexity to solve the optimization problem and the capacity to describe the dynamic aspects of the system. An MPC approach with quadratic cost function and without constraints may fall in the LQR (Linear Quadratic Regulator) problem. However, in [76], it has been proved that an MPC subjected to constraints can be approximate to a constrained LQR controller with weights matrix Q and R related to the state and control variables. In [77], a Quadratic Program problem can be solved with an LQR optimization model or with an MPC.

The MPC is used in different areas to evaluate complex dynamical systems. In [78], the authors demonstrated the recent growing interest in MPC applications in different contexts. In the energy sector, the MPC is not commonly adopted; however, in literature, there are some examples where MPC algorithms has been successfully applied. For example, in [79], a MPC algorithm is used to find the optimal solution to pump water using electric energy. Other applications are related to power and energy management in electric vehicles [80–82]. In [83], the authors proposed an MPC strategy to manage a power split between combustion engines and electrical vehicles. In this case, the focus of the system was to minimize fuel consumption, while studying all the constraints; the MPC was used to calculate an index to guarantee the assumptions. Recently, the advantages of MPC use were demonstrated in applications related to energy saving in the framework of heating and cooling systems for building [84–87].

2.3. Model Predictive Control Methods in Protected Agriculture

MPC approaches represent the main interesting strategies to control the indoor microclimate of the greenhouse. A large number of literature is dedicated to this field to monitor and control the different parameters and variables of the internal environment. The main studies focus on developing a control

approach to manage thermal or dynamic systems in order to reduce energy consumption [88,89]. The main complexities in the MPC control are:

- Identification of non-linearities in the dynamic system to correctly model the processes
- Design of the prediction module able to forecast controlled variables
- Choice of the control variables to be used in the optimization module to define the optimal control law

From an energy saving viewpoint, the MPC algorithm is largely used with state variables associated to indoor temperature or humidity, evaluating energy balance or water consumption. In [90], a data-driven robust model predictive control (DDRMPC) is developed to control greenhouse temperature. In [91], a MPC based on a mixed logical dynamical (MLD) model is used to control the greenhouse temperature-humidity system, taking into account the input disturbances related to outside temperature and humidity and solar radiation. In [88], the cost function aimed to maintain the divergence of temperature and humidity in respect to a range of suitable values in order to minimize energy and water consumption. Other approaches proposed to track the indoor temperature in respect to a reference trajectory operating on the control variables related to heating and ventilation by different methodologies such as genetic algorithms (GA) [92], particle swarm optimization algorithm (PSO) [93,94], sequential quadratic programming [95], or a combination of MPC and a feedback linearization technique [96]. The authors in [93] presented a particle swarm optimization framework based robust MPC control scheme for greenhouse temperature systems. The framework is formulated on a constrained nonlinear temperature problem. The findings demonstrate that the controller achieved the set point with the existence of disturbances and provided greater control precision, and powerful robustness than the classical MPC. In [97], centralized and distributed MPC controller performances are compared with a control manual system, taking into account the prediction models of the solar energy system, the water production system, and consumption in the greenhouse system. The authors concluded that the proposed MPC approached increased 5% in terms of thermal efficiency of the facility in comparison with a manual operation. Other studies proposed models to control greenhouse heating system by using a computational fluid dynamics (CFD) approach [98,99]. In [98], the energy prediction model (EPM) based on thermal balance is implemented to evaluate energy demand and system performance. Other MPC strategies have been implemented to control greenhouse temperature manipulating natural ventilation [100]. In addition, adaptive control techniques are used in the literature to optimize greenhouse crop production [101]. In order to decrease water use, the authors in [102] implemented an MPC control to optimize water production by a desalination plant according to the irrigation water crop demand. An exhaustive review on MPC approaches in agriculture application appears in [103]. It is important to underline that in these MPC approaches, the forecast model plays a fundamental role, and the decision whether to apply a simple linear forecasting model or a more complex one as in [104] is a key issue in MPC.

From an energetic viewpoint, the microgrid concept has been widely implemented in different sectors; however, despite their efficiency, there are limited investigations and applications in the agriculture sector considering greenhouses-powered microgrids. In microgrid applications, several works have concentrated on smart energy management frameworks and optimal control techniques to save energy and water. The authors of [105] formulated an optimization problem based on a robust distributed control scheme for a team of cooperating microgrids. The authors in [106] developed an MPC framework to optimally control the power exchanges among connected microgrids. The authors in [107] presented a linear quadratic formulation-based control strategy to control the stored energy and energy exchanges between microgrids. The authors in [108] investigated the cooperative energy management in networked microgrids. In [109], the authors solved an optimization problem based on Pontryagin's minimum principle formalization for power management in interconnected microgrids.

In the greenhouse context, many authors have suggested the adoption of MPC schemes to control climate environment in greenhouses, whereas, few papers have considered implementations of microgrids in agriculture, as well as networks of greenhouses. The authors of [110] investigated the possibility of considering an MPC to increase greenhouse indoor air temperature control. The design of a predictive control model using switch actuators as heater and ventilation windows to control greenhouse temperature has been investigated in [111]. The authors in [103] reviewed the introduction of MPC schemes as well as its applicability in agriculture. The authors stated that MPC development can be categorized into classical MPC, improved MPC, and the latest MPC. Furthermore, they concluded that smart agriculture will have a great future, thanks to the application of MPC techniques resulting from effective industrial applications. A Takagi–Sugeno fuzzy model-based MPC scheme of a greenhouse is reported in [112]. The model is used to consider nonlinear dynamics of the plant subject to parameter uncertainties. The authors in [113] developed an MPC scheme to enhance the control accuracy of actuators and decrease energy consumption in greenhouses. The authors formulated a multi-objective optimization problem-based cooperative game theory. The results show that the model is more efficient than single objective control schemes and classic linear weighted multi-objective control frameworks. Reference [114] is one of the first papers in the literature investigating the control of smart interconnected greenhouses integrated microgrid. The authors presented a comprehensive control strategy formulated as a constrained scheduling optimization framework embedded in an MPC scheme. The predictive algorithm is implemented to optimally control the complex interaction among climate variables defining microclimate environments.

From a comparative viewpoint, in [115], a closed-loop MPC strategy has been compared with an open loop control in tracking greenhouse climate variables associated with indoor temperature, humidity, and CO₂ concentration. The results demonstrated that MPC is superior in tracking the reference trajectories than the open loop control under the three different disturbances thresholds. In detail, for a system disturbance related to -2% and 2% of the variables values, the MPC, compared with open loop control, reduces the relative average deviation (RAD) by 60.06% for temperature tracking, 76.19% for relative humidity, and 78.12% for the CO₂ concentration. Besides, for a second performance index, associated to the maximum relative deviation (MRD), MPC reduces by 54.28% temperature MRD, 66.28% for relative humidity MRD, and 89.31% for the CO₂ concentration MRD. In a similar study, the authors compared the energy taking into account the control of the inside temperature of the greenhouse in respect to a predefined value and the heating pipe temperature in order to minimize energy consumption. In [92], the authors demonstrated the dominance of the MPC controller with respect to adaptive PI controllers. The latter solution fails in following the setpoints, especially during perturbation from the irradiance. On the contrary, MPC adapts the control to the requested values with limited oscillations around the tracking points. In [116], the MPC and PID strategies were compared in simplified soil–plant–atmosphere-model by a computer simulation related to the optimization of the soil water content (SWC) and the water irrigation amounts. The authors concluded that, in stable weather condition, MPC reaches the reference value of SWC in one day on a time horizon of 100 days, while PID needs about 10 days. Besides, if variable weather changes are considered, MPC reduces or increases with one day in advance the irrigation amounts according to predictions of precipitations with a real water-saving approach. On the contrary, the PID controller reacted with one day of delay in respect to the rain events, thus increasing the irrigation cost.

In [94], the performance of an MPC controller based on PSO and a conventional controller have been compared with the objective to maintain a predefined indoor greenhouse temperature, maximizing energy saving. The performance indices were related to the temperature set point accuracy (ER), energy consumption of heating E(H), energy consumption of ventilation E(V), standard deviation of heating control signal ($\sigma\Delta H$), and standard deviation of ventilation control signal ($\sigma\Delta V$) in a simulated scenario implemented in MATLAB. For 10 days of simulation, the MPC approach showed better results: 63.34% for ER, 64.96% for E(H), 77.72% for E(V), 40.63% for $\sigma\Delta H$, and 47.33% for $\sigma\Delta V$.

3. Future Perspectives

Control and systems technology will surely affect the future development of greenhouse cultivation, as new crop challenges in extreme environments surface. Some notes on these aspects are reported hereinafter to stimulate the readers on new researches in the field.

The main challenge in protected agriculture is to obtain an integrated system that can reduce energy, water, and pesticide consumption to achieve a zero net energy (ZNE) and water solution and realize a sustainable greenhouse system.

In [117], the authors proposed a semitransparent organic solar cells (OSCs) system to provide significant improvement in greenhouse efficiency and a surplus in energy production for greenhouses located in mild climate zones. The assumption that, among renewable energies, solar greenhouses seem to be the best technological strategy to implement a zero net energy solution depends on in-depth analysis of the specific environmental context in which it is located and on its design and building features. Site, orientation, geometries, glazing, shading, insulation, thermal storage, and artificial lighting represent the main elements of an efficient greenhouse [118], even in arid regions [119]. Other studies investigate the possibility to implement hybrid systems to realize a ZNE greenhouse; for example, the use of photovoltaic panels and ground source heat pump (GSHP) systems [120].

Water scarcity also represents a great problem in the farming sector, closely related to energy consumption and sustainability. Advanced technological solutions have been proposed in the last decade exploiting water treatment systems, which use grey water for irrigation, desalination, or dehumidification systems. Those solutions produce water-saving options but affect energy consumption. On the contrary, a new challenge in the sustainable management of irrigation water may be realized by the recovery of water with a closed loop system based on evapotranspiration from crops [121] or by adopting drip irrigation, adequate crop disposition in the space, and shorter crop cycles [122].

Among innovative greenhouse cultivation measures, vertical farming systems has to be cited. It consists of a sequence of vertical levels of cultivation, which provides substantial saving water and an insecticide-free environment, even if it needs the use of high degree of ICT control systems [123]. Another sustainable approach that merits consideration is the aeroponics method in which plants grow without soil and with a limited amount of water [124]. The water cycles, humidity, and other indoor parameters condition the development of pests in greenhouses and consequent pesticide use. The book in [125] represents a review in the context of greenhouse pest management.

The current requirements to cultivate in adverse meteorological conditions or due to land shortage pushed the researcher to study and implement alternative farming methodologies.

The Nemo's Garden® Project [126], started in 2012, implemented a new cultivation technique which supports plant growth in areas with unfavorable climate condition. The research group "Ocean Reef Group" developed a hydroponic farming system completely immersed in the sea. The proposed ecosystem consists of different greenhouses realized by transparent plastic biospheres that are located at 5–10 mt deep in the sea. The biospheres have a radius of about 2 m, and they contain 2000 L of air; they are a sort of transparent air balloons in which about 65–95 basil plants are positioned on shelves positioned inside. The prototype has been realized in a body of water in front of a small city called Noli in Liguria Region, Italy. There are numerous advantages to cultivating in an underwater closed environment which refer, above all, to the absence of insects, other plants, and parasites. The ICT control system is powered by solar panels and wind turbines that ensure the energy necessary for the monitoring devices. This solution completely avoids the use of pesticides and, besides, water for irrigation is self-provided, resulting from internal evaporation and condensation processes. The water is conveyed into a container and enriched with a fertilizer. A small pump takes the water to the highest part of the biosphere through a spiraling tube. The phytochemical analysis carried out by the researchers established limited phytochemical alterations of plants, which demonstrated their ability to adapt to a new habitat [127].

Even more extreme is the experiment realized by DLR (German Aerospace Center), which implemented the EDEN ISS project, which consisted of testing an innovative smart greenhouse facility for the proposed Mars mission using a bioregenerative life approach. In [128], the authors describe the characteristic of the space greenhouse station, which is meant to validate methodologies and technologies for safe fresh food production in adverse conditions in space. The greenhouse prototype is located in the German Neumayer III station in Antarctica. It is based on aeroponic cultivation equipped with led lighting systems, a detection system for bio properties and microbiological analysis, and a decontamination plant. The same research group also tested other innovative prototypes, such as Mars and lunar greenhouses integrating hydroponic cultivation and resource recycling systems for extraterrestrial applications [129].

4. Conclusions

It may appear astonishing that one of the most traditional and ancient human activities, that is agriculture, has been subject to a real digital revolution over the last few years. Buzzwords such as “digital agriculture”, “e-agriculture”, “precision agriculture”, and others are pushing the revolution process, where energy and water saving are a must on which such revolution is based. In smart greenhouses, new advanced control technologies will feed such revolution, and MPC is surely the control approach that will be more and more applied to save energy. The reason is quite simple: MPC finds its optimal application when the system dynamics can be modelled with reasonable approximation; in addition, it is sufficiently slow, with respect to the required time needed to perform the optimization. The flow of energy and power required in a greenhouse have similar characteristics. One possible further interesting field of research is the adoption of collaboration control schemes among different greenhouses, which may offer resources such as power production from PV glasses, water storage, and thermal heating. In this case too, MPC seems particularly promising in the adoption of distributed approaches, as recently shown by [130].

Author Contributions: The authors' contribution is to be considered equal on all the topics presented. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the project ANTEA project, Edible Flowers: Innovations for the Development of a Cross-Border Sector” developed in the framework of the Interreg ALCOTRA Programme between ‘Italy—France’ (2016–2020).

Acknowledgments: We thank the reviewers for their important contributions.

Conflicts of Interest: The authors declare no conflict of interest.

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