# Multi-Objective Load Dispatch Control of Biomass Heat and Power Cogeneration Based on Economic Model Predictive Control

**Lianming Li [1,2,\*], Defeng He [3], Jianrong Jin [2], Baoyun Yu [2] and Xiang Gao [1]**

[1] State Key Lab of Clean Energy Utilization, Zhejiang University, Hangzhou 310027, China; xgao1@zju.edu.cn
[2] Jiaxing New Jies Heat & Power Co., Ltd., Jiaxing 314016, China; jjr22071@126.com (J.J.); jiesyby@163.com (B.Y.)
[3] College of Information Engineering, Zhejiang University of Technology, Hangzhou 310023, China; hdfzj@zjut.edu.cn
[\*] Correspondence: lilianming@zju.edu.cn; Tel.: +86-189-5738-5368

**Abstract:** This paper proposes a multi-objective load dispatch algorithm based on economic predictive control to solve the real-time multi-objective load dispatch problem of biomass heat and power cogeneration. According to the energy conservation law and production process, a real-time multi-objective load dispatch optimization model for heat and power units is established. Then, the concept of multi-objective utopia points is introduced, and the multi-objective load comprehensive objective function is defined to coordinate the conflict between the economic performance and pollutant emission performance of the units. Furthermore, using the online receding optimization characteristics of economic predictive control, the comprehensive objective function of multi-objective load dispatching is optimized online. Then, the fuel rate satisfying the economic performance and pollutant emission performance of the units is calculated to realize the economic performance and environmental protection operation of biomass heat and power cogeneration. Finally, the proposed multi-objective load dispatch control method is compared to traditional dispatch strategies by using industrial data. The results show that the method presented here can well balance the production cost and pollutant emission objective under the fluctuation of the thermoelectric load demand, and provides a feasible scheme for real-time dispatching of the multi-objective load dispatch problem of biomass heat and power cogeneration.

**Keywords:** biomass heat and power cogeneration; multi-objective load dispatch; economy; pollutant emission; economic model predictive control

## 1. Introduction

With the progress of the "five waste co-governance" work in China, it is urgent to find a reasonable disposal method for biomass energy of agricultural and forestry wastes originally discarded, piled up, or burned in the open fields. Cogeneration of heat and power (CHP) can reasonably dispose of this part of the waste, which not only can reduce the waste of resources and optimize the structure of China's energy supply, but also solve the problem of environmental pollution and then improve the ecological environment. Now, CHP is becoming an increasingly important way to develop biomass resources' comprehensive utilization [1–4]. In CHP industry, the principle of fixing electricity by heat is usually adopted and the thermal load of CHP plants determines the operating load of the unit. However, the thermal load of CHP generally has the characteristics of large fluctuation between day and night [3,5], which requires the load of units to be adjusted accordingly. On the premise of keeping the thermal parameters stable, the load dispatch among multiple units will directly affect the efficiency and economy of unit operation [6,7]. Although pollutant emissions are low in biomass CHP systems [1,2], the emission of major pollutants, such as nitrogen oxides and sulfur compounds, still needs to be strictly controlled due to the state's "ultra-low emission" environmental protection policy. Therefore, the optimal

load allocation of biomass CHP is essentially a multi-objective collaborative optimization control problem involving economic and environmental objectives.

Conventional load optimal dispatch control approaches are mostly based on the unit operation economy under typical running conditions by establishing the operation economic costs and load optimization model of units. Then, the allocated load of each unit is calculated by minimizing the operation costs [5–7]. However, available studies show that there is conflict between the operating economic costs of CHP units and the quantities of pollutant emissions (such as $SO_2$, NOx, etc.) [5–9]. Therefore, the multi-objective load dispatch control mainly takes the fuel consumption and pollutant discharge under different load conditions as the optimal dispatching objectives, which are used to compute the optimal solution to the multi-objective load dispatch problem of each CHP unit. Server optimization methods, e.g., mixed integer programming, genetic algorithm, and particle swarm optimization, are commonly exploited to study the multi-objective load dispatch problem of CHP units [3,10–12]. In general, these multi-objective load dispatch algorithms assume that each CHP unit is in the steady-state combustion and implement off-line the optimal load allocation of CHP units. However, with the development of the electric power industry in the direction of smart and environmental protection in recent years, various new energy sources are connected to power generation and heat network systems. Meanwhile, with the increasing number of thermal users in CHP industry, the fluctuation of thermal load of the biomass cogeneration system has become more prominent [13]. Note that it is easy to dispatch a load of biomass CHP if the size of each unit consisting of the biomass CHP plant is exactly the same. However, in the actual industrial production process, the size of each unit is generally different from the other's due to the time-varying changes of thermal users' loads. Especially, some units are specialized in power generation while others are cogeneration of heat and power with different types of boimass fuels. In this case, the efficiencies of the units are different and then the dispatch load of the plants will directly affect the economy of the whole CHP plant. Therefore, to improve the economy (including saving costs of pollution emissions) of load dispatch of CHP units, it is necessary to introduce the multi-objective dispatch load method with real-time processes of the units to solve the load dispatch of biomass CHP units.

In recent years, economic model predictive control (EMPC) has been applied to real-time optimization of multi-objective power loads in power systems due to its ability to explicitly handle constraints and on-line multi-objective optimization in the systematical framework of optimal control [14–16]. Generally speaking, EMPC integrates the real-time process control and economic performance optimization into an optimal control framework, where it predicts the future behaviors of a system based on a model of the system and adopts the principle of receding horizon control to realize the closed-loop economic optimal control of the system [17,18]. Now, EMPC has been widely used to achieve economic optimization control in the energy, power, and other fields [19–21]. To the best of our knowledge, however, there are no implementations of EMPC in the multi-objective load dispatch control of biomass CHP plants.

This paper proposes an EMPC-based multi-objective load dispatch control strategy for the solution of the load dispatch control problem of biomass CHP plants. Based on the conservation of energy, a kinetic model of the thermal power and fuel rate of CHP units is established. Then, the objective functions are designed to formulate the operation economic costs and pollutant emission performance of CHP units. Because of the contradiction between economic performance and pollutant discharge performance, the concept of multi-objective utopia-point is introduced to define the multi-objective comprehensive objective function of the load dispatch problem of the CHP units. Based on the online receding horizon optimization characteristics of EMPC for the integrated objective function of load dispatch, the fuel rate is calculated to realize the economic and environmental operation of biomass cogeneration by satisfying the economic performance and pollutant discharge performance of the CHP units. Finally, the validity of the proposed load dispatch method is illustrated by a simulation experiment based on industrial field data.

## 2. Problem Description

Consider $n$ CHP units of a CHP factory, consisting of $n_1$ generator units, $n_2$ cogeneration units, and $n_3$ heating units and satisfying $n_1 + n_2 + n_3 = n$. Let index set $I$, $I_e$, $I_c$, and $I_h$ denote the numbers of the generator units, cogeneration units, and heating units. We assume that the real-time closed-loop control system of the whole CHP plant has a good control performance. Namely, the real-time controllers of units, arranged in the lower layer of the control system, have the ability to quickly and accurately adjust the process variables of the CHP plant. Moreover, it is assumed that the thermal load demand of each CHP unit is calculated by the principle of "thermostatic electricity", i.e., the amount of produced electricity is determined by the amount of supplied heat. According to the conservation of energy, the thermal power and fuel feed rate of the ith unit satisfy the following dynamic equation [4]:

$$\dot{P}_i(t) = \frac{1}{\tau_i}[\alpha_i H_i^v Q_i(t) + (1 - \alpha_i) H_i^c Q_i(t) - P_i(t)] \tag{1}$$

where $P_i$, $Q_i$, $\alpha_i$, $H_i^v$, $H_i^c$, and $\tau_i$ are the thermal power, fuel feed rate, proportion of volatile fuel, volatile calorific value, solid fuel calorific value, and time constant of the $i$th unit, respectively, $i \in I$. Furthermore, let number $\gamma_i$, $0 \leq \gamma_i \leq 1$ be the proportion of the thermal power accounted for the generated electricity to the total thermal power of the $i$th CHP unit.

The goal of multi-objective optimization of biomass thermoelectric loads is to compute the load dispatch scheme for optimizing the operation economy and pollutant emissions of the whole plant units within the constraint range of the decision variables on the basis of meeting the stability of the thermal load of units. Therefore, it is necessary to formulate the performance index functions of the unit operation economy, pollutant discharge, and fuel supply.

In the process of biomass cogeneration, fuel consumption and other comprehensive operating costs are usually used to describe the economic performance of the unit. Consider the $i$th biomass CHPC unit, the following quadratic fitting curves are used to define the unit operating cost [5,13]:

$$G_i(P_i(t)) = a_{i,1} P_i^2(t) + a_{i,2} P_i(t) + a_{i,3} \tag{2}$$

where $G_i$ is the fuel consumption amount per kWh of the $i$th CHP unit; and $a_{i,1}$, $a_{i,2}$, and $a_{i,3}$ are the characteristic coefficients of the fuel consumption amount per kWh. The pollutant discharge performance of the unit is similar to the economic performance of the unit. The following three fitting curves are used to describe the pollutant discharge [5,13]:

$$W_i(P_i(t)) = b_{i,1} P_i^3(t) + b_{i,2} P_i^2(t) + b_{i,3} P_i(t) + b_{i,4} \tag{3}$$

where $W_i$ is the emission of flue gas pollutants ($SO_2$, $NO_x$, etc.) from the $i$th CHP unit; and $b_{i,1}$, $b_{i,2}$, $b_{i,3}$, and $b_{i,4}$ is the emission characteristic coefficient of pollutants. These characteristic coefficients can be calculated by the field data fitting [5,6,10,13].

The optimal load distribution of the CHP units is also limited by the load demands of units and users. Let $P_e(t)$ and $P_h(t)$ be the total power load and the total heat load demand in the $t$ dispatching period, respectively. The total power load demand and the total power generation balance in each dispatching period satisfy the balance constraints:

$$\sum_{i=1}^{I_e} P_i(t) + \sum_{j=1}^{I_c} \gamma_j P_j(t) = P_e(t) \tag{4}$$

In each scheduling period of CHP, the constraints on the total heat load demand and total heating power balance are described by:

$$\sum_{i=1}^{I_h} P_i(t) + \sum_{j=1}^{I_c} (1 - \gamma_j) P_j(t) = P_h(t) \tag{5}$$

Furthermore, the constraints of heating power of each unit are defined by:

$$P_{i,\min} \leq P_i(t) \leq P_{i,\max}, \; \forall i \in \pmb{I}, \; t \geq 0 \tag{6}$$

and the constraints of the fuel feed rate of each unit satisfy that:

$$Q_{i,\min} \leq Q_i(t) \leq Q_{i,\max}, \; \forall i \in \pmb{I}, \; t \geq 0 \tag{7}$$

where the subscripts 'min' and 'max' represent the lower limit and upper limit of the corresponding variables, respectively.

The goal of this work is to compute the optimal combustion quantity $Q_i$ and the optimal power load $P_i$ of each unit in real time to minimize the operating cost and pollutant discharge of the whole plant CHP units subject to the constraints on the heating power and fuel feed rate of the biomass thermal power units (6) and (7), the total electricity load (4), and the total thermal load demand (5). In this study, the economic model predictive control and multi-objective utopia-point method are combined to design the multi-objective load dispatch control strategy for biomass plant CHP units.

## 3. Multi-Objective Load Dispatch Control

In the process of biomass power and heat cogeneration, the users' thermal load instructions delivered by power grid dispatch systems are transmitted power plants. Then, according to the actual operation situations and the historical data of each unit, the power plant uses its dynamic model to predict the future generating thermal power of units and the fuel rate over a period of time. By collecting the actual data of the parameters of the control systems, the operation cost, and the pollutants discharge, the economic receding horizon control and multi-objective utopia-point optimization are used to real-time calculate the heat load of each unit by taking into account the multiple objectives of economy and environmental protection. Moreover, the load regulation ability and pollution reduction degree of each unit are analyzed to get the optimal control strategy for the load dispatch and fuel feed rate of each unit. This operation achieves the economic and environmental goals of the biomass cogeneration whole process of the plant.

### 3.1. Prediction Model Based on State Space

Consider the thermal power dynamics model (1) of the biomass CHP unit and select the state variable $x = [P_1, \dots, P_n]^{\mathrm{T}}$ and the control variable $u = [Q_1, \dots, Q_n]^{\mathrm{T}}$. From (1), one can obtain the state space model approximated to the discrete-time state space model:

$$x(k+1) = Ax(k) + Bu(k) \tag{8}$$

where diagonal matrices $A = \mathrm{diag}\{1 - T_s/\tau_1, \dots, 1 - T_s/\tau_n\}$ and $B = \mathrm{diag}\{(\alpha_1 H_1{}^v + (1 - \alpha_1)H_1{}^c)T_s/\tau_1, \dots, (\alpha_n H_n{}^v + (1 - \alpha_n) H_n{}^c)T_s/\tau_n\}$ and discrete scheduling time period $T_s > 0$.

Let $u_N(k) = [u(0|k)^{\mathrm{T}}, \dots, u(N-1|k)^{\mathrm{T}}]^{\mathrm{T}}$ be the control sequence of future $N$ actions at the current moment $k$. Applying $u_N(k)$ to the system (8), the predicted state variables of the system over $N$ steps are computed as:

$$x_N(k+1) = \varphi_x x(k) + \varphi_u u_N(k) \tag{9}$$

where state variable sequence $x_N(k) = [x(1|k)^{\mathrm{T}}, \dots, x(N|k)^{\mathrm{T}}]^{\mathrm{T}}$ and matrices:

$$\varphi_x = \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^N \end{bmatrix}, \; \varphi_u = \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N-1}B & A^{N-2}B & \cdots & B \end{bmatrix}$$

According to the prediction state Equation (9), the thermal power values of CHP units in the future $N$ steps can be obtained under the input of fuel quantity $u_N(k)$.

### 3.2. Multi-Objective Load Dispatch Controllers

The goal of load dispatch control of CHP units is to achieve the economic and environmental objectives of the biomass cogeneration process for the whole plant. Therefore, according to the prediction Equation (9), the operating cost objective function and pollutant discharge of the whole plant units in the future window $[k, k + N]$ are separately predicted by:

$$
\begin{aligned}
J_G(k) &= \sum_{s=0}^{N-1} \sum_{i=1}^{n} G_i(x_i(s|k)) \\
&= \sum_{s=0}^{N-1} \sum_{i=1}^{n} a_{i,1} x_i^2(s|k) + a_{i,2} x_i(s|k) + a_{i,3}
\end{aligned}
\tag{10}
$$

$$
\begin{aligned}
J_W(k) &= \sum_{s=0}^{N-1} \sum_{i=1}^{n} W_i(x_i(s|k)) \\
&= \sum_{s=0}^{N-1} \sum_{i=1}^{n} b_{i,1} x_i^3(s|k) + b_{i,2} x_i^2(s|k) + b_{i,3} x_i(s|k) + b_{i,4}
\end{aligned}
\tag{11}
$$

Due to the conflict between production costs and pollutant emission targets, the steady-state utopia-point of the functions $J_G$ and $J_W$ are denoted by $(G_s{}^*, W_s{}^*)$, which are separately calculated by:

$$
G_s^* = \min_{(x,u) \in M_{ss}} \sum_{i=1}^{n} a_{i,1} x_i^2 + a_{i,2} x_i + a_{i,3}
\tag{12}
$$

$$
W_s^* = \min_{(x,u) \in M_{ss}} \sum_{i=1}^{n} b_{i,1} x_i^3 + b_{i,2} x_i^2 + b_{i,3} x_i + b_{i,4}
\tag{13}
$$

where $M_{ss}$ is the steady-state constraint set of state variables and control variables of the unit CHP process, i.e.,

$$
M_{ss} = \left\{ (x,u) \left|
\begin{array}{l}
x = Ax + Bu \\
\sum_{i=1}^{I_h} x_i + \sum_{j=1}^{I_c} (1 - \gamma_j) x_j = P_h \\
\sum_{i=1}^{I_c} x_i + \sum_{j=1}^{I_c} \gamma_j x_j = P_e \\
P_{i,\min} \le x_i \le P_{i,\max},\ i = 1, \ldots, n \\
Q_{i,\min} \le u_i \le Q_{i,\max},\ i = 1, \ldots, n
\end{array}
\right. \right\}
\tag{14}
$$

Correspondingly, the steady-state solutions of minimal values $G_s{}^*$ and $W_s{}^*$ are calculated as $(x_G, u_G)$ and $(x_W, u_W)$, respectively. Due to the conflict between the two targets $J_G$ and $J_W$, the load dispatch control of the CHP units cannot reach the utopia-point $(G_s{}^*, W_s{}^*)$ at the same time. Therefore, the compromise steady-state solution $(x_s, u_s)$ is calculated by:

$$
(x_s, u_s) = \arg \min_{(x,u) \in M_{ss}} \left\| \begin{bmatrix} G_s^* - \sum_{i=1}^{n} G_i(x_i) \\ W_s^* - \sum_{i=1}^{n} W_i(x_i) \end{bmatrix} \right\|_p
\tag{15}
$$

where $||\bullet||_p$ is the $p$ norm of the vector, that is, the compromise solution is the steady-state load power and fuel rate of the CHP units with the closest target performance to the utopia-point $(G_s{}^*, W_s{}^*)$ in the sense of $p$ norm.

Considering the load power $x(k)$ at the current moment $k$, a multi-objective comprehensive cost function based on the utopia-point $(G_s{}^*, W_s{}^*)$ is defined as:

$$
J(k) = \left\| \begin{matrix} J_G(k) - NG_s^* \\ J_w(k) - NW_s^* \end{matrix} \right\|_p + \sum_{s=0}^{N-1} u^{\mathrm{T}}(s|k) R u(s|k)
\tag{16}
$$

where $R > 0$ is the positive definite matrix weighting the control variables over the horizon window $[k, k + N - 1]$, which is used to penalize the fluctuations of the fuel rate of the CHP

units. Then, the multi-objective load dispatch control problem of the biomss CHP units is formulated as the following finite-time optimal control problem:

$$
\begin{aligned}
u_N^*(k) = \arg\min_{u_N(k)} &\, J(k) \\
s.t.\ x(s+1|k) =&\, Ax(s|k) + Bu(s|k) \\
\textstyle\sum_{i=1}^{I_h} x_i(s|k) + \sum_{j=1}^{I_c}(1-\gamma_j)x_j(s|k) =&\, P_h(k) \\
\textstyle\sum_{i=1}^{I_e} x_i(s|k) + \sum_{j=1}^{I_c}\gamma_j x_j(s|k) =&\, P_e(k) \\
P_{i,\min} \le x_i(s|k) \le&\, P_{i,\max},\ i=1,\dots,n \\
Q_{i,\min} \le u_i(s|k) \le&\, Q_{i,\max},\ i=1,\dots,n \\
x(0|k) =&\, x(k),\ s=0,\dots,N-1 \\
x(N|k) =&\, x_s
\end{aligned}
\tag{17}
$$

where $x(0|k) = x(k)$ is the initial condition of optimization, $x(N|k) = x_s$ is the terminal constraint condition, and $u_N^*(k)$ is the optimal solution at the current moment of $k$. Note that the terminal constraint condition is used to improve the stability of the closed-loop system. The nonlinear numerical programming algorithms, such as sequence quadratic programming (SQP) and particle swarm optimization [10], can usually be exploited to online solve the optimization problem (17). According to the receding optimization principle of EMPC, the multi-objective load dispatch controller of the biomass CHP system is defined as $u(k) = u^*(0|k)$ and the corresponding closed-loop system is determined by $x(k+1) = Ax(k) + Bu^*(0|k)$ for all time instants $k \ge 0$.

Because of the conflict between the operating costs and pollutant emission objectives, the comprehensive objective function (16) is not a positive definite function about the deviation of the compromise equilibrium point $(x_s, u_s)$. Hence, it will not be equal to zero when the states of the CHP units arrive at the compromise equilibrium point and the optimization problem (17) then becomes a standard economic model predictive control problem. It is noted that the system (8) is a linear system, and the objective function (16) is a regular function [22]. Therefore, the system (8) and the function (16) can satisfy the strong duality assumption or dissipativity condition [14,22]. By combining the terminal equality constraint $x(N|k) = x_s$ or directly imposing the stability contractive constraint [23], the asymptotic stability of the closed-loop system $x(k+1) = Ax(k) + Bu^*(0|k)$ can be ensured. It should be noted that the multiplier method to deal with the terminal equality constraint can reduce the computational burden of online solving the problem (17) and meanwhile, the equilibrium point $(x_s, u_s)$ satisfies the constraint conditions of optimization (17). Moreover, the triplet of MPC [17] can be used to ensure the recursive feasibility of the optimization problem in (17).

Remark 1: Note that conventional multi-objective load dispatch methods of biomass CHP units usually require adjustment of the weights of the operating cost and pollutant emission objective functions, which depends on the designer's experience and is subject to some subjective factors. In this work, the proposed method employs the utopia-point of the two objectives as the reference and then defines the multi-objective comprehensive objective function by employing the concept of $p$ norm distance to the function closest to the utopia-point. It can fully avoid manual selection of the weights of the operation cost and pollutants emission target function and then reduce the dependence on the designer's experience and subjectivity.

Remark 2: Most of the existing multi-objective load dispatch methods for biomass CHP units adopt the steady-state optimization model to offline distribute the loads of the units, which ignored the thermal power generation dynamics model of each unit. In this paper, the proposed method applies the thermal power generating dynamic model to predict the operation cost and pollutant emissions of each unit based on the current information of the cogeneration unit and grid scheduling. Hence, the proposed load dispatch method optimizes the load allocation and fuel input rate of each unit in an online

receding horizon fashion. As a result, the efficiency and quality of load dispatch of biomass CHP units have been improved.

### 3.3. Procedure of Multi-Objective Load Dispatch Control

The procedures of the multi-objective load dispatch controller of the biomass CHP units, which is defined by the optimal control problem (17), are summarized as follows:

(1)  Initialize the predictive horizon $N>0$ and weighted matrix $R$, and define the comprehensive objective function of multi-objective load dispatch of the CHP units (16); let $k = 0$.
(2)  Measure the user's thermal load $P_h(k)$ and $P_e(k)$ at the time instant $k$. If the user's heat loads do not change, then go to step 3); otherwise, compute the steady-state utopia-point $(Gs^*, Ws^*)$ of the economic operation cost and pollutant emission objectives from (12) and (13), and then calculate the compromise equilibrium point $(x_s, u_s)$ of the cogeneration system for the CHP units from (15).
(3)  Measure the state $x(k)$ at the current time and obtain the optimal solution $u_N^*(k)$ by solving the optimization problem (17).
(4)  Take the first component of the optimal solution $u^*(0|k)$ to apply to the power cogeneration system (8) of biomass CHP units.
(5)  Set $k = k + 1$ and return to Step 2.

Note that in principle, the multi-objective load dispatch control method proposed in this work is also suitable for, e.g., diesel of natural gas CHP, but differences exist in the fuel grade influences only at the heating value and the coefficients values in Equations (1)–(5). However, biomass fuels are more preferable for use as the fuel of CHP than diesel fuels of natural gas in China.

## 4. Results and Discussion

In order to verify the effectiveness of the method presented in this paper, four biomass cogeneration units are considered, where the first is the extracting and condensing steam turbine equipped with an air-cooled generator unit, the second and third are cogeneration transverse circulating fluidized bed boilers, and the last is the transverse heating circulating fluidized bed boiler. The model parameters of each unit are presented in Table 1, where the values of $a_{i,j}$ and $b_{i,s}$ for $i = 1, \ldots, 4$, $j = 1, 2, 3$, and $s = 1, \ldots, 4$ were mainly followed from [5,6,10,13] while taking into account the real CHP plants in China.

**Table 1.** Model parameters of units.

| Parameters | 1# | 2# | 3# | 4# |
|---|---|---|---|---|
| $\alpha_i$ (%) | 59.6 | 59.6 | 59.6 | 59.6 |
| $H_i^c$ (kJ·kg$^{-1}$) | 10465 | 10465 | 10465 | 10465 |
| $H_i^v$ (kJ·kg$^{-1}$) | 5880 | 5880 | 5880 | 5880 |
| $\tau_i$ (s) | 600 | 360 | 360 | 600 |
| $\gamma_i$ | 1 | 0.8 | 0.7 | 0 |
| $P_{i,\min}$ (MW) | 6 | 10 | 5 | 10 |
| $P_{i,\max}$ (MW) | 15 | 25 | 12 | 25 |
| $Q_{i,\min}$ (kg·s$^{-1}$) | 0 | 0 | 0 | 0 |
| $Q_{i,\max}$ (kg·s$^{-1}$) | 8.5 | 12 | 7.5 | 12 |
| $a_{i,1}$ | 0.003 | 0.003 | 0.003 | 0.003 |
| $a_{i,2}$ | 1.8 | 1.8 | 1.8 | 1.8 |
| $a_{i,3}$ | 60.0 | 60.0 | 60.0 | 60.0 |
| $b_{i,1}$ | $1.65 \times 10^{-5}$ | $1.65 \times 10^{-5}$ | $1.65 \times 10^{-5}$ | $1.65 \times 10^{-5}$ |
| $b_{i,2}$ | $5.64 \times 10^{-4}$ | $5.64 \times 10^{-4}$ | $5.64 \times 10^{-4}$ | $5.64 \times 10^{-4}$ |
| $b_{i,3}$ | $-6.05 \times 10^{-4}$ | $-6.05 \times 10^{-4}$ | $-6.05 \times 10^{-4}$ | $-6.05 \times 10^{-4}$ |
| $b_{i,4}$ | $2.54 \times 10^{-4}$ | $2.54 \times 10^{-4}$ | $2.54 \times 10^{-4}$ | $2.54 \times 10^{-4}$ |

In the simulation, let the dispatch control period $T = 5$ min, the weight matrix of control $R = 0.1I_4$, the prediction horizon $N = 6$, and the simulation time is 1200 min. In addition, we assume that the profiles of the user's heat load $P_h(k)$ and $P_e(k)$ are set as follows:

$$P_e(k) = \begin{cases} 20, & 0 \leq k \leq 60T_s \\ 25, & 60T_s \leq k \leq 120T_s \\ 30, & 120T_s \leq k \leq 180T_s \\ 25, & 180T_s \leq k \leq 240T_s \end{cases}$$

$$P_h(k) = \begin{cases} 15, & 0 \leq k \leq 60T_s \\ 20, & 60T_s \leq k \leq 120T_s \\ 30, & 120T_s \leq k \leq 180T_s \\ 20, & 180T_s \leq k \leq 240T_s \end{cases}$$

The corresponding curve is shown as the dotted line in Figure 1. Then, from (12) and (13), one can calculate the utopia-points of the economic operation cost and pollutant emission objectives within each time period as $(G_s{}^*, W_s{}^*) = (303.9537, 0.2382)$, $(322.5704, 0.4246)$, $(351.0246, 0.8906)$, and $(322.5704, 0.4246)$, respectively. The corresponding equilibrium points are determined from (15) as $(x_s, u_s) = ([6.26, 12.798, 5, 10.94]^T, [0.8098, 1.6551, 0.6466, 1.4149]^T)$, $([8.366, 15.304, 6.273, 15.057]^T, [1.0819, 1.9792, 0.8113, 1.9473]^T)$, $([9.225, 17.705, 9.445, 23.626]^T, [1.193, 2.2897, 1.2215, 3.0554]^T)$ and $([8.366, 15.304, 6.273, 15.057]^T, [1.0819, 1.9792, 0.8113, 1.9473]^T)$.
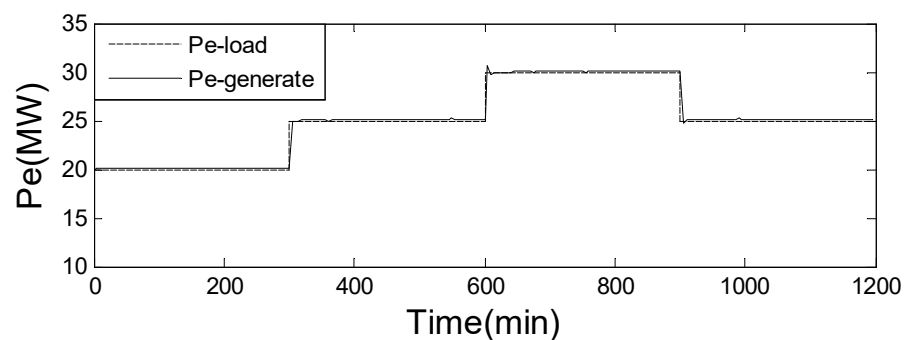


**Figure 1.** Electric load and power supply of the whole plant.

In the simulation, it is assumed that the thermal power unit is operating stably under the optimal condition in the first stage $[0, 60T_s]$. Then, according to the user's thermoelectric load demand, the states and controls of each unit are $x(k) = [6.262, 12.798, 5.000, 10.940]^T$ and $u(k) = [0.8098, 1.6551, 0.6466, 1.4149]^T$ for $k \in [0, 60T_s]$. Figures 1 and 2 show the response trajectories of the power supplied by the whole plant to the thermoelectric load, respectively. In Figure 1, the dotted lines and the solid lines are the demand power of the electric load and the power supply response curve of the whole plant for the CHP units, respectively. In Figure 2, the dotted lines and the solid lines are the demand power of the thermal load and the power supply response curve of the whole plant for the CHP units, respectively. It can be observed from Figures 1 and 2 that the proposed method can track the changing heat and power demand quickly and accurately.

Figures 3 and 4 show the state responses and control input profiles of each CHP unit, i.e., the trajectories of thermal power and the fuel rate, respectively, where the solid lines, dotted lines, dotted lines, and dotted lines represent the results of the corresponding units 1 to 4, respectively. It can be observed from Figures 1–4 that the state responses and control input profiles of each CHP unit can satisfy the constraints of the CHP plant. Moreover, the thermal power and fuel rate of each CHP unit can be adjusted rapidly during the change of the heat-and-power load demand. Note that in order to lessen the step changes of load dispatch at the time instants of switching operation, one method is to limit the variations of the control $u$ at adjacent times in the optimization problem (17), i.e., adding

some constraints on the variations of the control variable. Finally, Figures 5 and 6 show the time evaluations of the instantaneous economic operation costs and pollutant emission quantities of each CHP unit, where the solid lines, dotted lines, dotted lines, and dotted lines represent the results of the corresponding units 1 to 4, respectively. It can be observed from Figures 5 and 6 that the economic operation costs and pollutant emission quantities of the load dispatch control scheme adopted in this paper are close to the utopia-point in each period. It indicates that the proposed method can effectively coordinate the economic operation costs and pollutant emission quantities of the cogeneration multi-objective load regulation and control.
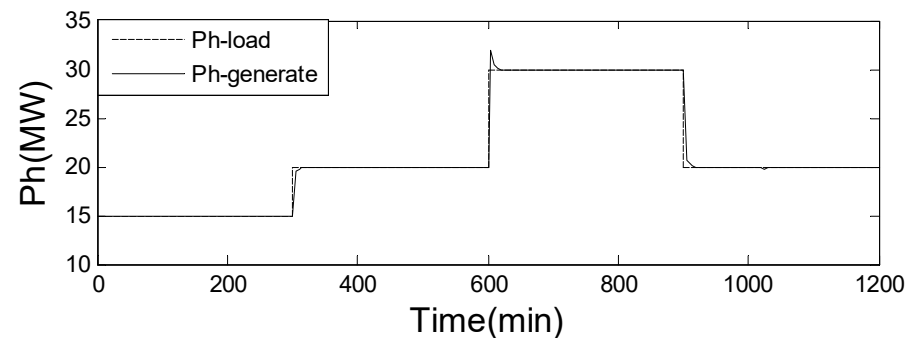


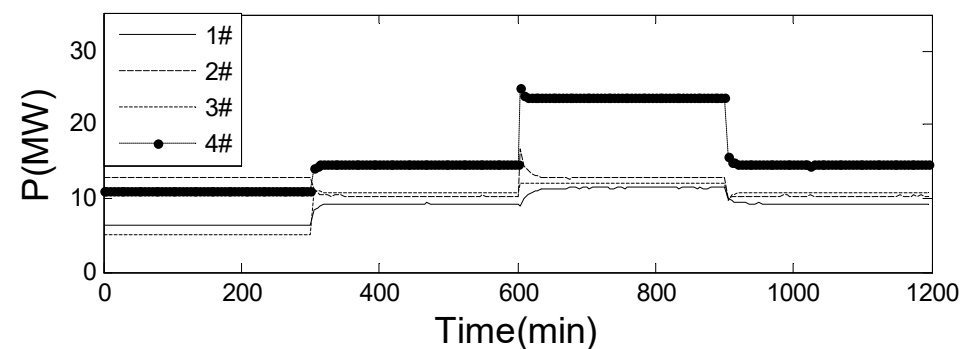**Figure 2.** Thermal load and power supply of the whole plant.



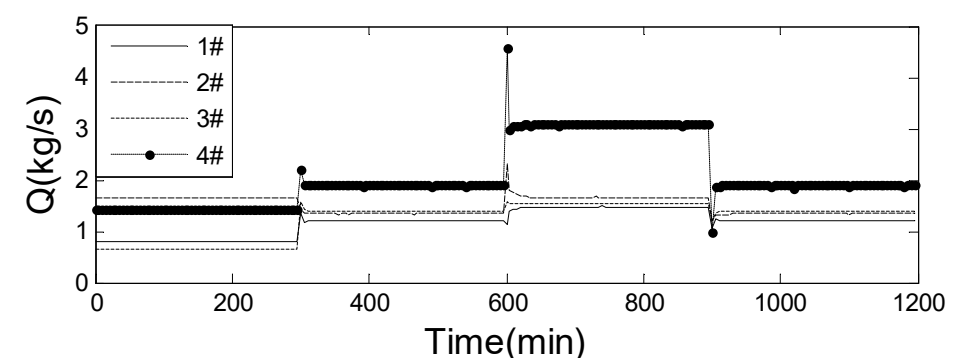**Figure 3.** State response curve of the CHP units.



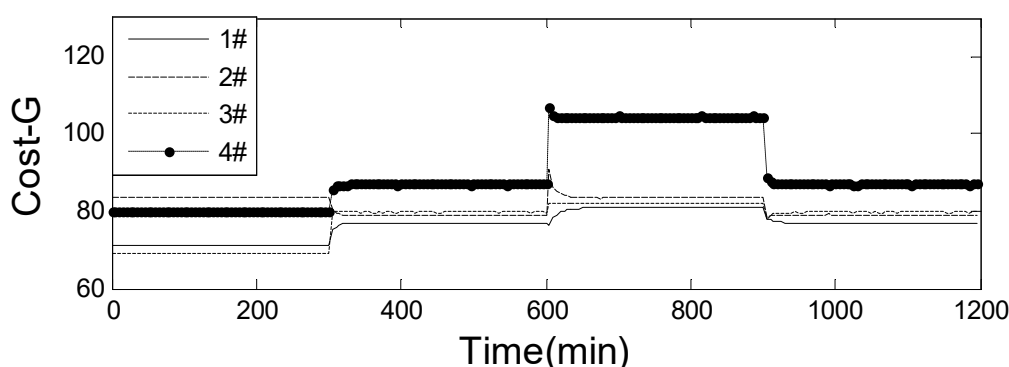**Figure 4.** Control input curve of the hot unit.

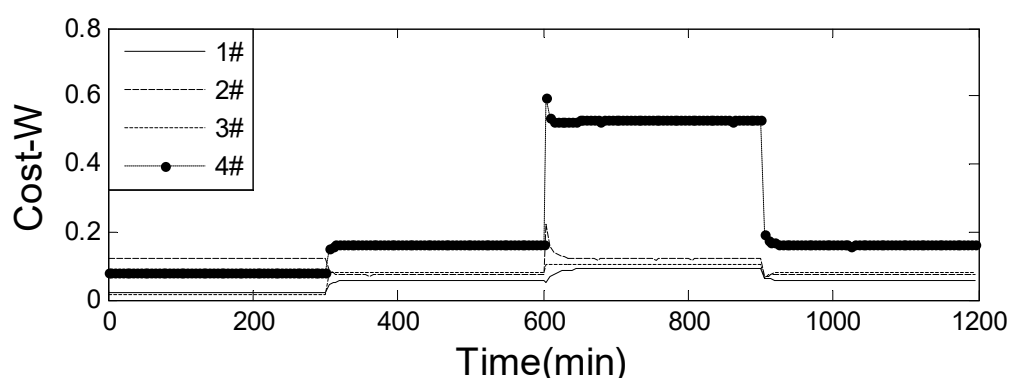**Figure 5.** Operation cost curve of the CHP units.



**Figure 6.** Pollutant emission curve of the CHP units.

In order to further evaluate the benefits of the proposed method in saving production costs and reducing pollutant emissions, the operators' experience-based dispatch method of CHP widely using the steady-state models is compared in terms of the average production cost 'Av-G' and average pollutant emission cost 'Av-W' of four biomass cogeneration units in four periods. Let 'Method1' and 'Method2' stand for the proposed method here and the operators' experience-based dispatch strategy, respectively. In Method2, two load dispatch solutions of CHP are adopted, where in Solution 1, the load dispatch of $i$th unit is prioritized than that of $(i + 1)$th unit, and in Solution 2, the loads of units are elaborately dispatched by a trial-and-error procedure to reduce pollutant emissions as low as possible. The loads dispatched by both solutions of Method2 are listed in Table 2. Then, the statistical results on Av-G and Av-W obtained by adopting Method1 and Method2 are shown in Tables 3–6, respectively. It can be firstly observed from Tables 3, 4 and 6 that the Av-G values of four units obtained by Solution 1 of Method 2 are less than that of Method1. This is resulted from the fact that the operating cost (2) has a constant term, which implies that the operating cost of a unit is not less than the constant cost once the unit is running, but in Solution 1 of Method2, at least one unit is closed in each time period. However, one can also observe from Tables 3, 4 and 6 that the Av-W values of four units obtained by Solution 1 of Method2 are solidly more than that of Method1, which leads to possibly violation of the standard of pollutant emissions. To this end, Solution 2 of Method2 elaborately dispatches the loads of units by a trial-and-error procedure in order to reduce pollutant emissions as low as possible. From Tables 3, 5 and 6, one can see that although the Av-W values of four units obtained by Solution 2 of Method2 are similar to those of Method1, the Av-G values are more than those of Method1. It is remarked that although Method1 and Solution 2 of Method2 have similar operation results, Solution 2 of Method2 has to depend on the experience of operators in the field, which is inevitably affected by human arbitrary factors, whilst Method1 can automatically compute the optimal load distribution of CHP plants whenever changing users' heat and power loads.

**Table 2.** Loads dispatched by Method2 in each period.

| Loads (Time Period) | Solution 1 | | | | Solution 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | 1# | 2# | 3# | 4# | 1# | 2# | 3# | 4# |
| (0, 300) | 15 | 20 | 0 | 0 | 13 | 8 | 6 | 9 |
| (300, 600) | 15 | 0 | 10 | 20 | 15 | 10 | 10 | 10 |
| (600, 900) | 15 | 25 | 0 | 20 | 10 | 20.5 | 9.5 | 20 |
| (900, 1200) | 15 | 0 | 10 | 20 | 15 | 10 | 10 | 10 |

**Table 3.** Average performance of units in each period by Method1.

| Performance (Time Period) | 1# | | 2# | | 3# | | 4# | |
|---|---|---|---|---|---|---|---|---|
| | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W |
| (0, 300) | 71.3891 | 0.0226 | 83.5271 | 0.1195 | 69.0750 | 0.0134 | 80.0519 | 0.0827 |
| (300, 600) | 76.8277 | 0.0555 | 79.0518 | 0.0737 | 79.5537 | 0.0786 | 86.8520 | 0.1623 |
| (600, 900) | 80.6566 | 0.0888 | 83.6863 | 0.1218 | 81.9920 | 0.1023 | 104.3083 | 0.5235 |
| (900, 1200) | 77.0822 | 0.0574 | 78.9943 | 0.0732 | 79.7148 | 0.0796 | 87.3349 | 0.1708 |

**Table 4.** Average performance of units in each period by Solution 1 of Method2.

| Performance (Time Period) | 1# | | 2# | | 3# | | 4# | |
|---|---|---|---|---|---|---|---|---|
| | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W |
| (0, 300) | 87.6750 | 0.1740 | 97.2000 | 0.3460 | 0 | 0 | 0 | 0 |
| (300, 600) | 87.6750 | 0.1740 | 0 | 0 | 78.3000 | 0.0671 | 97.2000 | 0.3460 |
| (600, 900) | 87.6750 | 0.1740 | 106.8750 | 0.5950 | 0 | 0 | 97.2000 | 0.3460 |
| (900, 1200) | 87.6750 | 0.1740 | 0 | 0 | 78.3000 | 0.0671 | 97.2000 | 0.3460 |

**Table 5.** Average performance of units in each period by Solution 2 of Method2.

| Performance (Time Period) | 1# | | 2# | | 3# | | 4# | |
|---|---|---|---|---|---|---|---|---|
| | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W |
| (0, 300) | 83.9070 | 0.1240 | 74.5920 | 0.0400 | 70.9080 | 0.0205 | 76.4430 | 0.0525 |
| (300, 600) | 87.6750 | 0.1738 | 78.3000 | 0.0671 | 78.3000 | 0.0671 | 78.3000 | 0.0671 |
| (600, 900) | 78.3000 | 0.0671 | 98.1608 | 0.3670 | 77.3708 | 0.0600 | 97.2000 | 0.3458 |
| (900, 1200) | 87.6750 | 0.1738 | 78.3000 | 0.0671 | 78.3000 | 0.0671 | 78.3000 | 0.0671 |

**Table 6.** Total performance of units in each period by different methods.

| (Time Period) Performance | (0, 300) | | (300, 600) | | (600, 900) | | (900, 1200) | |
|---|---|---|---|---|---|---|---|---|
| | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W | Av-G | Av-W |
| Method1 | 304.0431 | 0.2382 | 322.2852 | 0.3701 | 350.6432 | 0.8364 | 323.1262 | 0.3810 |
| Solution1 | 184.8750 | 0.5200 | 263.1750 | 0.5900 | 291.750 | 1.1150 | 263.1750 | 0.5900 |
| Solution2 | 305.8500 | 0.2370 | 322.5750 | 0.3751 | 351.0315 | 0.8394 | 322.5750 | 0.3751 |

## 5. Conclusions

This paper proposed a multi-objective load dispatch control method for allocating loads of units of biomass CHP plants based on the economic model predictive control technology. By adopting the online receding horizon optimization principle of EMPC, the control objective functions describing the energy consumption trend of the units are optimized to accommodate the multi-objective load dispatch of the units dynamically and quickly. The energy saving algorithm can determine the optimum fuel intake under the condition of reducing production cost and pollutant emissions of the CHP units by no adjustment of the weights of each cost function in the objective function. Simulations on the MatLab platform verified that

the proposed method can effectively reconcile the conflict between the production cost and pollutants emissions under the fluctuations of the user's load demand and fuel price. Therefore, the proposed method provided a feasible scheme for the multi-objective load dynamic dispatch control of biomass CHP plants. Since the operation reliability is always important and the response/transition time exists inevitably during biomass conversion plants, the future work pursued is to study the effects of operation reliability and the delay time on the load dispatch control of CHP plants.

**Author Contributions:** Conceptualization, L.L.; methodology, L.L.; software, D.H.; validation, J.J., B.Y. and X.G.; formal analysis, L.L. and D.H.; investigation, J.J.; resources, J.J.; data curation, D.H.; writing—original draft preparation, L.L. and D.H.; writing—review and editing, B.Y. and X.G. All authors have read and agreed to the published version of the manuscript.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

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

# References

1. Osaki, M.R.; Seleghim, P. Bioethanol and power from integrated second generation biomass: A Monte Carlo simulation. *Energy Convers. Manag.* **2017**, *141*, 274–284. [CrossRef]
2. Kortela, J.; Jämsä-Jounela, S.-L. Modeling and model predictive control of the BioPower combined heat and power (CHP) plant. *Int. J. Electr. Power Energy Syst.* **2015**, *65*, 453–462. [CrossRef]
3. Xu, D.; Ding, Q.; Huang, G.D.; Dai, S. Cogeneration unit dynamic scheduling model considering peak-load regulation ability. *Power Syst. Prot. Control* **2017**, *45*, 59–64.
4. He, D.; Zhang, Y.; Xu, S.; Li, L. Multi-objective economic predictive control of biomass CFBB combustion process. *High Technol. Lett.* **2019**, *29*, 668–674. (In Chinese)
5. Liu, J.; Liu, B.-H.; Zhang, Y.; Ma, B.-B.; Liu, C.; National Engineering Laboratory for Biomass Power Generation Equipment; North China Electric Power University; China Justice Big Data Institute CO., Ltd.; School of Energy and Power Engineering; North China Electric Power University; et al. Energy-saving and environmental protection multi-target load dispatching of thermal power plants based on big data technology. *J. Eng. Thermophys.* **2020**, *41*, 29–38.
6. Ahmadi, A.; Ahmadi, M.R.; Nezhad, A.E. A lexicographic optimization and augmented ε-constraint technique for short-term environmental/economic combined heat and power scheduling. *Electr. Power Compon. Syst.* **2014**, *42*, 945–958. [CrossRef]
7. Liang, J.; Li, G.; Wang, J. Double-objective heat and power dispatch based on lexicographic optimization method and ε-constraint technique. *Therm. Power Gener.* **2017**, *46*, 81–87.
8. Yang, Z.P.; Li, K.R.; Wang, N.L.; Jin, Z.; Song, S.; Guo, X. A model of considering the economic analysis and environmental protection for thermal power compensation on peak regulation. *J. Eng. Thermophys.* **2018**, *39*, 2124–2130.
9. Chen, N.-N.; Han, X.; Mu, Q.-W.; Liu, M.; Yan, J.-J. Environmental impact assessment on 1000 MW coal-fired power plant under off-design conditions. *J. Eng. Thermophys.* **2019**, *40*, 22–27.
10. Basu, M. Combined heat and power economic emission dispatch using nondominated sorting genetic algorithm-II. *Int. J. Electr. Power Energy Syst.* **2013**, *53*, 135–141. [CrossRef]
11. Peng, C.; Sun, H. Multi-objective optimization power dispatch based on non-dominated sorting differential evolution. *Proc. Chin. Soc. Electr. Eng.* **2012**, *29*, 71–76.
12. Sheng, W.X.; Ye, X.S.; Liu, K.Y.; Meng, X.L. Optimal allocation between distributed generations and microgrid based on NSGA-II algorithm. *Proc. Chin. Soc. Electr. Eng.* **2015**, *35*, 4555–4562.
13. Shi, B.; Yan, L.-X.; Wu, W. Multi-objective optimization for combined heat and power economic dispatch with power transmission loss and emission reduction. *Energy* **2013**, *56*, 135–143. [CrossRef]
14. Liu, X.; Cui, J. Economic model predictive control of boiler-turbine system. *J. Process Control* **2018**, *66*, 59–67. [CrossRef]
15. Pereira, M.; Limon, D.; de la Pena, D.M.; Valverde, L.; Alamo, T. Periodic economic control of a nonisolated microgrid. *IEEE Trans. Ind. Electron.* **2015**, *62*, 5247–5255. [CrossRef]
16. Clarke, W.C.; Manzie, C.; Brear, M.J. Hierarchical economic MPC for systems with storage states. *Automatica* **2018**, *94*, 138–150. [CrossRef]
17. Wolf, I.J.; Marquardt, W. Fast NMPC schemes for regulatory and economic NMPC—A review. *J. Process Control* **2016**, *44*, 162–183. [CrossRef]

18. Risbeck, M.J.; Rawlings, J.B. Economic model predictive control for time-varying cost and peak demand charge optimization. *IEEE Trans. Autom. Control* **2020**, *65*, 2957–2968. [CrossRef]
19. Alessandretti, A.; Aguiar, A.P.; Jones, C.N. On convergence and performance certification of a continuous-time economic model predictive control scheme with time-varying performance index. *Automatica* **2016**, *68*, 305–313. [CrossRef]
20. He, D.; Zhang, Y.; Li, L.; Qiu, X. Lexicographic economic predictive control without terminal constraints form CFBB combustion systems. *J. Chem. Ind. Eng.* **2020**, *71*, 1210–1216. (In Chinese)
21. Qi, Y.; Wang, W.; Xiang, C.; Zhao, Y. Economic MPC-based transient control for a dual-mode power-split HEV. *Sci. China Ser. E Technol. Sci.* **2017**, *60*, 1917–1934. [CrossRef]
22. Angeli, D.; Amrit, R.; Rawlings, J.B. On average performance and stability of economic model predictive control. *IEEE Trans. Autom. Control* **2012**, *57*, 1615–1626. [CrossRef]
23. He, D.; Yu, S.; Ou, L. Lexicographic MPC with multiple economic criteria for constrained nonlinear systems. *J. Frankl. Inst.* **2018**, *355*, 753–773. [CrossRef]