A Model Predictive Control for Cotton Farm Microgrid Systems in Australia

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***Abstract*— This paper presents a model predictive control (MPC) approach to a microgrid at a cotton farm so as to minimize the water pumping operational cost while taking full advantage of renewable energy sources. The reason for using MPC is its ability in handling noise, disturbance, and real-time parameter changes. In this paper, the MPC models of grid-connected are established; moreover, the effectiveness and robustness of the MPC models are analyzed by cotton farm case studies. Simulation results show that the optimal MPC solutions for grid-connected microgrid of a farm are AU$8.4/ML less than a manual control-based strategy. In addition, the MPC solution shows outstanding robustness in controlling the water reservoir level. When the disturbance data of the rainy season in 2016 are added, the system saves 34.5% of the operating cost compared with the baseline. When the rainy season disturbance is added together, the system saves 11.74% of operating costs compared to the baseline.**

Keywords*— *Cotton farm, MPC, grid-connected microgrid, PV, Pump, Reservoir

I. INTRODUCTION

Hybrid renewable energy irrigation systems have been widely applied in the agricultural sector in Australia. Cotton farming has a good opportunity to take advantage of renewable energy sources (RESs) as an alternative energy source to meet high energy demand during irrigation [1]. The number of microgrid systems composed of renewable generation, energy storage units and traditional energy sources is increasing in Australian agriculture sector, and has brought enormous benefits to agricultural development [2]. When the hybrid renewable energy system is combined with optimal operation technology, the renewable energy source can be used more efficiently, and more operating costs can be saved.

II. LITERATURE REVIEW

A. Related work

A variety of optimized operation technologies have been adopted to solve energy dispatch problems in order to save operating costs. For example, the proportional-integral feedback control scheme in [3], the fuzzy logic control load shift method in [4], the direct power control and optimization in [5], and an open-loop pump scheduling method in [6]. Nevertheless, these optimization techniques used in [7] do not include feedback and possible re-optimization. From the perspective of control theory [8], these applications do not observe the output of the control process. Therefore, the robustness and stability of the system will be inferior to the closed-loop optimization system. Note that model predictive control (MPC) is a powerful closed-loop optimal control strategy for a moving optimization horizon [9], and it has been successfully applied in microgrids to provide stable and efficient operations [10]. Generally, MPC is a control method which optimizes the predicted future system behavior under explicit constraints, and derives the optimal control sequence at each control horizon [11]. After implementing the first element of the calculated control solution, the controller moves to the next prediction horizon window and iteratively solves the optimization problem [12]. In addition, robustness is an important feature of MPC, which makes the system inherently stable in the face of uncertainty. The robust MPC is mainly to design an optimization-based control methodology that explains between uncertainty and systems, constraints, and performance criteria in a tractable way [13]. The linear robust MPC and nonlinear robust MPC numerical method have been proved by the convex approximation of MPC in [14].

B. Main contributions

This paper aims to propose an MPC approach to solve the cotton farm microgrid operation problem while taking into account the constraints of the Australian cotton growing industry, where a grid-connected model for a rural small microgrid will be established, and weather condition changes are used to conduct robustness and operating cost analysis. Furthermore, this MPC approach is developed to control microgrid energy dispatching, which can utilize renewable energy sources efficiently to save irrigation costs. The supply and demand balance model of the microgrid irrigation system under grid-connected mode is established. The main contributions of this study can be summarized as follows.

i. Cost minimization MPC models for a microgrid in a cotton farm are established for the grid-connected mode. This model can reduce operating costs by optimally controlling the pumps in the cotton farm.

ii. MPC methodology is adopted for cotton microgrid control, which optimizes not only the on/off state of the water pumps, but also the feed-in state of the grid-connected case for cost-saving purposes.

iii. A case study is carried out using real energy consumption data from an Australian cotton farm, and the impacts of MPC operations on the grid-connected microgrid is analyzed, which provides insights for the microgrid investment and development for Australian cotton farms. Furthermore, the proposed MPC operational strategy can also minimize the dependence on conventional energy sources and promote renewable energy.

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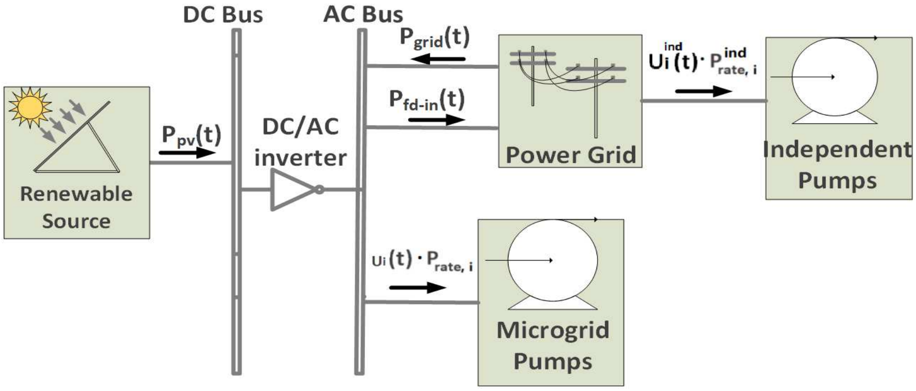

Fig.1. Grid-connected hybrid-power microgrid configuration

The remaining parts of this paper are organized as follows. Section III introduces the MPC models of the microgrid in the cotton farm irrigation system, and the optimisation model for the grid-connected mode is formulated for the microgrid. The MPC algorithm and the closed-loop optimization methodology are also explained in this section. Section IV demonstrates the implementation of the proposed MPC algorithm in a case study. Finally, the conclusions are drawn from this study and summarized in Section V.

III. A CONTROL MODEL FOR COTTON FARM MICROGRID OPERATION

In Australia, the energy consumption of pumping water is up to 30% of the total direct energy of the cotton industry [15]. Therefore, microgrid integrated with renewable energy sources is a viable solution to reducing the energy cost in cotton farms. In a grid-connected microgrid system, as shown in Fig. 1, renewable energy is mainly composed of solar energy, which is connected to the utility grid through a DC-AC inverter. The microgrid provides electric energy to the water pump, the insufficient energy is purchased from the grid, and the excess energy of the microgrid is fed into the grid. The pumps connected to the microgrid are called microgrid pumps, and the pumps directly supplied by the grid are called independent pumps, as shown in Fig. 1.

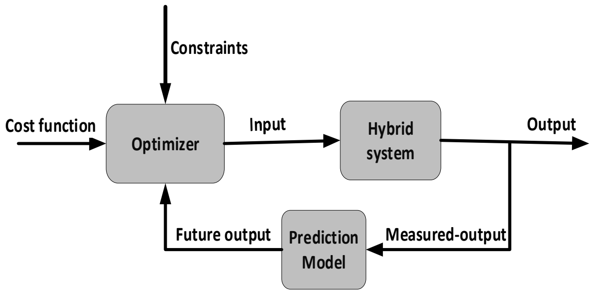

Fig.2. MPC closed-loop model

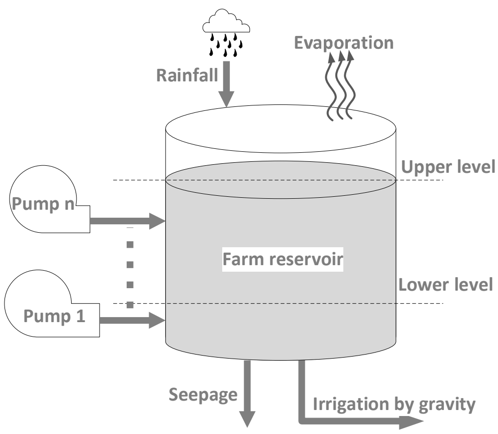

Fig. 3. Farm water storage components and water balance model

A. MPC loops for the hybrid system

The basic MPC closed-loop method is shown in Fig. 2. Fig. 2 shows that the optimal control problem is solved repeatedly over a moving finite prediction horizon, and only the first control element is executed after each iteration. In the next sampling interval, the new state of the hybrid power system (i.e., renewable and conventional power) is sent to the prediction model, and the optimization process is repeated. In addition, output feedback and optimizing the corresponding solution can provide a stable solution against uncertainties caused by external disturbances. For example, excessive water is supplied due to the rainy season or uncertain evaporation, which can lead to uncertainties in water demand.

B. Water balance model

The water balance model can be described by a simplified first-order model which is shown in Fig. 3. In Fig. 3, the changes in the water level of the reservoir are caused by inflow (pumping and precipitation) and outflow (evapotranspiration and irrigation). This relationship is simplified by the following equations.

$$S(t+1) = S(t) + Inflow(t) - Outflow(t) \tag{1}$$

$$Inflow(t) = \sum_{i=1}^{L} \frac{u_i(t)\cdot P_{rate,i}\cdot \Delta t}{E_{con,i}\cdot H_i} + \sum_{i=1}^{L^{ind}} \frac{u_i^{ind}(t)\cdot P_{rate,i}^{ind}\cdot \Delta t}{E_{con,i}^{ind}\cdot H_i^{ind}} + V_R(t) \tag{2}$$

$$Outflow(t) = F_0(t) + V_L(t) \tag{3}$$

$$u_i(t)\ \left(\text{or } u_i^{ind}(t)\right) = \begin{cases} 0, & when\ pump\ is\ off \\ 1, & when\ pump\ is\ on \end{cases} \qquad t = 1,\cdots,T \tag{4}$$

s.t.

$$\sum_{i=1}^{L}\frac{u_i(t)\cdot P_{rate,i}\cdot\Delta t}{E_{con,i}\cdot H_i}+\sum_{i=1}^{L^{ind}}\frac{u_i^{ind}(t)\cdot P_{rate,i}^{ind}\cdot\Delta t}{E_{con,i}^{ind}\cdot H_i^{ind}}\le\frac{V_{max}\cdot\Delta t}{24} \tag{5}$$

$$S_{min}\le S(t)\le S_{max} \tag{6}$$

where one hour is taken as the sampling period Δt, t represents the sampling time, and T is the length of prediction horizon. $S(t)$ denotes the water volume in the reservoir at the t^{th} hour which is bounded by the upper bound $S_{max}(ML)$ and lower bound $S_{min}\ (ML)$. Eq. (1) is the water balance equation of the water $Inflow(t)$ and $Outflow(t)$ of the reservoir. In (2), $Inflow(t)$ equals the pumped water from all the pumps at t^{th} hour, plus the amount of precipitation $V_R(t)$; $P_{rate,i}$ is the rated power of the i^{th} pump which is connected to the microgrid; $P_{rate,i}^{ind}$ is the rated power of the i^{th} independent pump which is directly connected to a conventional energy source (grid or diesel generator); $E_{con,i}$ and $E_{con,i}^{ind}$ and the potential energy needed to lift 1 ML of water for one meter of height, and $E_{con,i}=E_{con,i}^{ind}=4.55kWh/m$ [16] in this case; H_i and H_i^{ind} are the height (meter) of the lifting water of the pump; and L and L^{ind} are the total number of the microgrid pumps and independent pumps, respectively. In (3), $F_0(t)$ is the volume of water flowing from the reservoir to cotton field by gravity at the t^{th} hour, and $V_L(t)\ (ML)$ is the total water loss by evaporation and seepage at the t^{th} hour. $u_i(t)$ and $u_i^{ind}(t)$ in (4) are the control variable and are the binary on/off switching status of the pump at the t^{th} hour. In (5), V_{max} is the maximum water volume per 24 hours [17] that is allowed to be accessed from a specified water source (e.g., bore or river) and used for irrigation. Hence, Eq. (1) can be rewritten as (7).

$$S(t+1)=S(t)+\sum_{i=1}^{L}\frac{u_i(t)\cdot P_{rate,i}\cdot\Delta t}{E_{con,i}\cdot H_i}+\sum_{i=1}^{L^{ind}}\frac{u_i^{ind}(t)\cdot P_{rate,i}^{ind}\cdot\Delta t}{E_{con,i}^{ind}\cdot H_i^{ind}}+V_R(t)-F_0(t)-V_L(t) \tag{7}$$

C. Hybrid-power microgrid model

Based on Fig. 1, a grid-connected microgrid does not need to use the diesel generator due to its high cost. Hence, the grid-connected power balance model can be expressed in (8):

$$P_{pv}(t)+P_{grid}(t)=\sum_{i=1}^{L}u_i(t)\cdot P_{rate,i}+P_{fd-in}(t) \tag{8}$$

$$P_{pv}(t)=\alpha\cdot P_{pv}^{0}(t) \tag{9}$$

s.t.

$$0\le P_{grid}(t)\le\eta_G(t)\cdot P_{pump}^{max} \tag{10}$$

$$0\le P_{fd-in}(t)\le[(1-\eta_G(t))]\cdot P_{fd-in}^{max} \tag{11}$$

where $P_{pv}(t)\ge 0$ represents the total generated power from renewable energy source at the t^{th} hour; $P_{grid}(t)\ge 0$ is the power flowing from utility grid to the pump loads at the t^{th} hour; $P_{fd-in}(t)\ge 0$ is the amount of excess power at the t^{th} hour fed-in to the grid; α is the number of the renewable energy source to be installed; $P_{pv}^{0}(t)$ is the power output of a single renewable source at the t^{th} hour; P_{pump}^{max} is the maximum power consumption of all the pumps; $\eta_G(t)$ is the binary variable denoting the direction of grid power flow which equals 1 when $P_{grid}(t)>0$ and 0 otherwise; P_{fd-in}^{max} is the maximum feed-in power allowed to the grid.

D. Optimization model

In the following, we define the cost function F(t) for the grid-connected mode of microgrid.

$$F(t)=\left[P_{grid}(t)+\sum_{i=1}^{L^{ind}}u_i^{ind}(t)\cdot P_{rate,i}^{ind}\right]\cdot\Delta t\cdot\mathrm{C}(t)-P_{fd-in}(t)\cdot\Delta t\cdot\mathcal{B}(t) \tag{12}$$

Here, $\mathrm{C}(t)$ is the grid energy price at the t^{th} time (e.g., TOU tariff (AU$/kWh)); $\mathcal{B}(t)$ is the feed-in tariff.

a) Open-loop optimal control model

In order to reduce the operating cost within the prediction horizon (T) (e.g., 24 hours), the open-loop optimization model is expressed as (13),

$$\min_{u_i,u_i^{ind}}\sum_{t=1}^{T}F(t) \tag{13}$$

b) Closed-loop optimal control model

Using the same model as the open-loop MPC model in (13), the objective function of the closed-loop MPC optimal control model can be obtained below.

$$\min_{u_i,\,u_i^{ind}}\sum_{t=1+m}^{T+m}F(t) \tag{14}$$

where the interval of $[m+1,\cdots,T+m]$ means that the prediction horizon and the closed-loop MPC optimization is an iterative implementation over the prediction horizon. This objective function (14) will satisfy similar constraints like (8)-(11) over the new time horizon $[m+1,\cdots,T+m]$.

IV. Case Study

The proposed MPC approach is applied to compare two different operation types of cotton farm irrigation pump systems (baseline manual control and MPC) in this case study.

A. Cotton farm background

The studied cotton farm is located in the south of Gunnedah, New South Wales, Australia. The farm has two sub-bore electricity pumps, each with the nominal power of 75 kW, and a 37kW electric re-lift pump, which lift water from Mooki river. One electric 75 kW bore pump is directly connected to the grid, and the microgrid is equipped with an electric 75 kW bore pump and 37 kW electric re-lift pump as well as a 50.6 kW solar system [18]. In 2016, this pumping system pumped water 1,004 ML from the bore and 247 ML from the river, and the maximum pumping volume is 30 ML/day in the irrigation season [19]. This study focuses on the high irrigation water demand period for the cotton farm, which lasts approximately 87 days from November to January. As shown in Fig. 4, the control model needs to determine the optimal switching status of Pump #1, Pump #2 and Pump #3 to minimize electricity charge during the entire irrigation period.

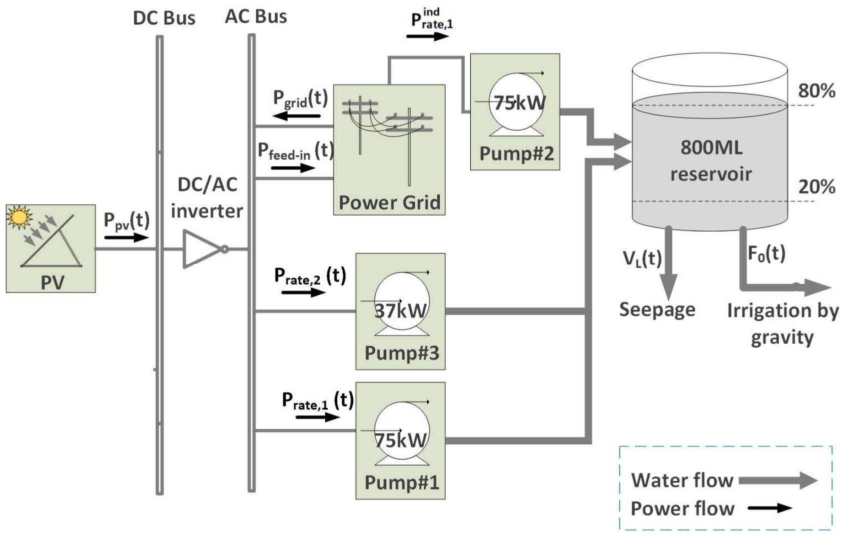

Fig. 4. Grid-connected microgrid simulation model

B. Baseline electricity operating costs

The owner of this cotton farm installed a 50.6 kW solar PV system to power the bore lifting pump. The owner commonly performs the control of the pump and determines the pumping time and duration based on personal experience. According to the current water demand for crop watering, the farmer intervenes to set each pump-to-pump water at a specific start time or for a specific duration. Table I shows the calculated electricity cost for the entire pumping scheme in 2016.

TABLE I. ENERGY COST BREAKDOWN OF THE COTTON FARM IN 2016

Items	Value	Unit
Pump #1 75kW operation time	1034	Hours
Pump #2 75kW operation time	882	Hours
Pump #3 37kW operation time	360	Hours
Pump #1 energy consumption	75,812.33	kWh
Pump #2 energy consumption	63,551.06	kWh
Pump #3 energy consumption	12,865.24	kWh
Pump #1 electricity cost	19,711.2	AU$
Pump #2 electricity cost	16,523.3	AU$
Pump #3 electricity cost	3,345.0	AU$
Pump #1 pumping water	537.5	ML
Pump #2 pumping water	450.5	ML
Pump #3 pumping water	235.6	ML

C. Assumptions of closed-loop control model

This model uses the closed-loop MPC method to control the operation of the pumping system of the cotton farm in 2016, in order to achieve the reduction of the operating cost. The following assumptions are made.

a) The microgrid pumps #1(75 kW), #3(37 kW) and an independent pump #2 (75 kW) are considered in the optimal control model.
b) River water or bore water has to be pumped into the reservoir, and then crops are irrigated from the reservoir. Therefore, the microgrid pumps and the independent pump are controlled based on the water level of the reservoir.
c) The load factor is one. This means that the pump motors run at the maximum load when they are switched on.
d) Historical irrigation data of the cotton farm in 2016 are taken.
e) The problem analyzed in this case is solved using MATLAB and YALMIP. The CPLEX solver is used to solve this linear integer optimization problem.
f) The cotton irrigation period in 2016 is 87 days. In order to compare with the original operating costs, the total computation horizon is set to 87 days in this case.
g) In the baseline manual control case.1, $V_R(t) = V_L(t) = 0$, which means that the baseline case only considers the irrigation outflow from the reservoir.

D. Robustness validation in the cotton farm

The disturbance is a period of abundant rainfall. Rainfall in the cotton farm area can be found in the Australian Government Bureau of Metrology (BOM). According to 30 years of historical climate data, the cotton farm is located in an area where the average daily rainfall in summer is 25 mm/m^2 [20]. The total area of the 800 ML reservoir is about 10 Ha. Through the rainfall data provided by the BOM in 2016, we add rainfall as a disturbance to the original MPC model. Therefore, an increase in the reservoir water volume and a decrease in the irrigation demand based on the rainfall data are observed. Then $V_R(t)$ can be expressed as (15), and (16) represents the rainwater collected in the cotton farm planting area at the t^{th} hour.

$$V_R(t) = R_{data}(t) \cdot \mathrm{Z}_{res} \cdot 0.01 \tag{15}$$

$$R_{area}(t) = R_{data}(t) \cdot \mathrm{Z}_{land} \cdot 0.01 \tag{16}$$

where $R_{data}(t)$ (mm/hour) are hourly precipitation data from BOM; Z_{res} is the reservoir surface area, Z_{res}=10 (Ha) in this case. And 0.01 means every millimetre per square meter rainfall equate to 0.01 ML/Ha. $R_{area}(t)$ is the amount of rainwater collected in the entire cotton farm area at the t^{th} hour; and Z_{land}=300 (Ha) is the farmland area. During the rainy season, the irrigation water demand $F_0(t)$ is defined as (17)

$$F_0(t) = \begin{cases} 0, \ when\ R_{data}(t) \geq F_0(t) \\ F_0(t) - R_{area}(t), \ when\ R_{data}(t) < F_0(t) \end{cases} \tag{17}$$

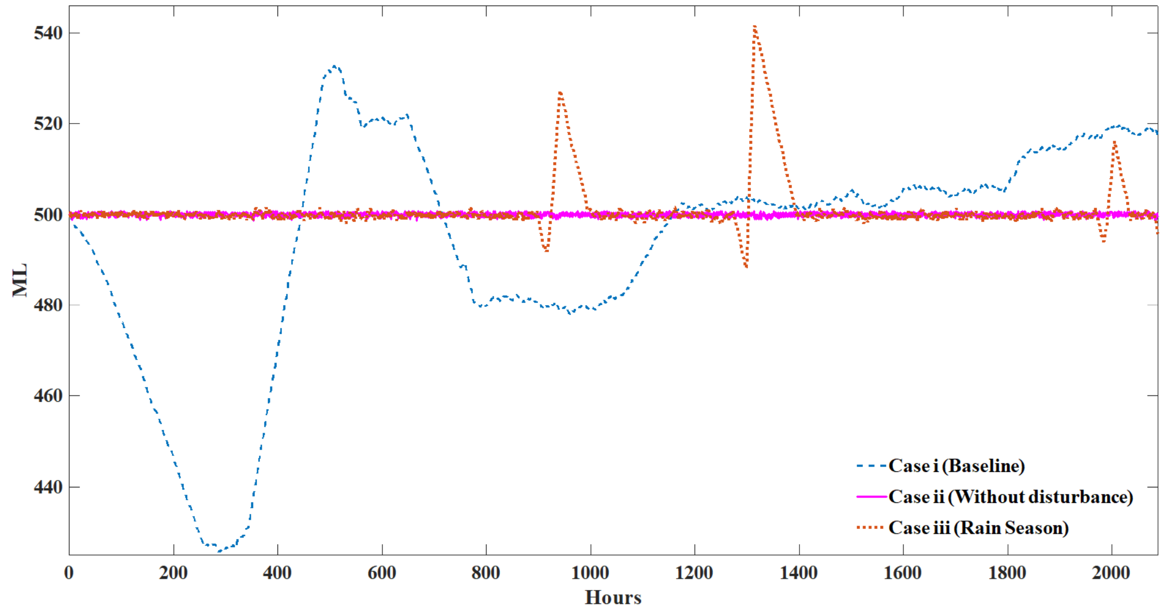

Fig. 5. Baseline and MPC with disturbance

E. Results and discussions

In order to show the performance of the proposed MPC in different operating modes, three different situations have been selected based on a fixed period (e.g., 87 days) of the cotton farm in the entire irrigation season, namely baseline (manual control), MPC and MPC with rainfall disturbance. The simulation runs on 2088 hours (87 days) of the computation horizon based on the 2016 historical irrigation data with a time interval of 1 hour, and the prediction horizon is 24 hours.

Table II shows the results of pump working hours, total operating costs, and the total volume of water that has been pumped in each scenario during the entire irrigation period. Fig. 5 shows the water level in the reservoir under different control modes during the entire irrigation period.

TABLE II. RESULTS OF DIFFERENT SCENARIOS IN THE ENTIRE IRRIGATION PERIOD

Cases	Pump #1 75kW		Pump #2 75kW		Pump #3 37kW	
	Work hours	***Water lift (ML)***	***Work hours***	***Water lift (ML)***	***Work hours***	***Water lift (ML)***
Baseline	1,034	537.5	882	450.6	360	235.6
MPC	770	409.4	1,132	601.9	1,056	715.6
Rain season	453	240.9	660	350.9	549	372.0

Based on Table II, the total operating cost of each situation and the average cost per ML in the above three modes can be calculated, as show on Table III.

TABLE III. TOTAL OPERATING COST AND AVERAGE PUMPING COST IN THE SIMULATION

Cases	Total operational cost (AU$)	Average pumping cost (AU$/ML)
Baseline	39,579.5	32.34
MPC	40,716	23.58
Rain season	23,184	24.05

Case i. Manual control method (the Baseline)

Baseline simulation is calculated based on the historical power consumption data of the farm's pumps, which is combined with the pumping height and the amount of water pumped per kWh of electricity. The farmer manually controls the three pumps based on personal experience. Fig. 5 shows that the working status of the water pumps. The Baseline operating cost during the entire irrigation period is AU$39,580, and the total amount of water pumped is 1,223.7 ML.

Case ii. MPC optimal control model – without disturbance

The MPC optimal control model is simulated during the entire irrigation period. At the end of each hour, the reservoir level is used as the initial reservoir level for the next hour. Fig. 5 shows the resulting curve of the closed-loop MPC optimal control model. Through the MPC algorithm, the operating cost optimization can be achieved by maintaining the water level of the reservoir at the current level. In Table III, the operating cost for the MPC scenario is AU$40,716 for the entire irrigation period, which is AU$1,136.5 higher than the baseline, but the amount of water pumped is 1,726.95ML. Therefore, the average operating cost is AU$8.8/ML lower than Baseline.

Case iii. MPC optimal control model – with rain season disturbance

The rainy season disturbance case is to add precipitation data from August 2016 to January 2017 to the MPC benchmark. Fig. 5 shows that there are three occurrences of heavy rainfall that caused significant changes in the reservoir water level (e.g., the precipitation up to 41mm/m^2 from December 23 to December 24, 2016, which is from 1300th to 1315th hours in Fig. 5). Due to the 24-hour prediction horizon, the closed-loop MPC solution controls the water pumps to stop working from the 1274th hour to the 1399th hour. Then the pumps keep on stopping until the water level drops to 500ML, and the pumps start to work again. Under the rainy season disturbance scenario, the operating cost during the entire irrigation period is AU$23,184, which is A$16,395.5, about 34.85% lower than the baseline, and the average operating cost is A$8.3/ML lower than baseline.

V. Conclusion

This paper introduces the MPC approach to the operating cost minimization problem for an Australian cotton farm microgrid. It also shows the robustness of the MPC algorithm under rainy conditions for the grid-connected microgrid. The results of the cotton farm case study show that the MPC approach reduces the operating cost of the grid-connected microgrid from AU$ 32.34/ML to AU$ 23.58/ML. The presented MPC solution can be combined with future weather forecast data to achieve the real-time operation and energy management of the microgrid in the cotton farm. As an immediate future study, voltage and frequency control of the cotton farm microgrid in the grid-connected and islanded modes considering uncertain renewable generations will be investigated.

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