On-line Optimal EMS Implementation for Distributed Power System

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Abstract

As the distributed power system with PV and ESS is highlighted to be one of the most prominent structure to replace the traditional electric power system, power flow scheduling is expected to bring better system efficiency. Optimal energy management system (EMS) where the power from PV and the grid is managed in time-domain using ESS needs an optimization process. In this paper, main optimization method is implemented using dynamic programming (DP). To overcome the drawback of DP in which ideal future information is required, prediction stage precedes every EMS execution. A simple auto-regressive moving-average (ARMA) forecasting followed by a PI-controller updates the prediction data. Assessment of the on-line optimal EMS scheme has been evaluated on several cases.

1. Introduction

Among many renewable energy sources (RES), PV generation is highlighted as its per-unit cost is anticipated to be cheaper than the conventional sources in near future. However, the limitation of PV penetration into the current grid induced by the intermittent property of PV has been addressed [1]. Integrating energy storage systems (ESS) into PV-system enables power shifting of PV output so that penetration of solar energy can be enhanced. For this reason, micro-grid power systems with PV and ESS are accounted as one of the most prominent configurations [2].

A simple configuration, equipped with one renewable energy source (RES) and one ESS, is, however, quite complex to manage the energy and power flow. The PV power is intermittent where it shows a high peak around noon, while the load curve usually has peaks at noon and evening. The system efficiency can be improved by power shifting which cuts the energy peak of PV output and delivers it to the evening load peak. The problem aroused is the energy management systems (EMS). [9].

Dynamic programming (DP) is widely applied to the EMS problems, such as hybrid electric vehicle (HEV) systems as well as distributed generation (DG) micro-grid systems [25], [26]. However, DP-based approaches have two main drawbacks, high computational time, and assumption on deterministic future information. The first drawback is less crucial for power system application where the time constant is large, tens of second to few minutes. Meanwhile, the accuracy of future information greatly affects the result of optimization process.

In this paper, a DP-based EMS optimization scheme is proposed. A prediction process is designed to bring a more precise application of DP [13]. The proposed method updates the forecasting data before every execution of EMS module. Auto-regressive moving-average (ARMA) model in time-series analysis is used to predict the next forecasting data, followed by a PI-control process to revise the previous prediction data. The method is simulated using MATLAB/Simulink.

2. System Description and Modeling

The composition of elements of the system and its configuration are described briefly in the Fig.1. A main computer centered in the figure commits EMS operation which delivers power flow schemes to each element. Followings are modelings of the components.

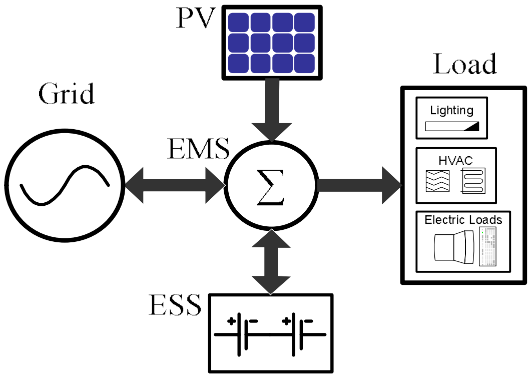

Fig. 1. Overview of the system configuration

Every PV module is assumed to be operated in maximum power point tracking (MPPT). PV output power is defined as,

$$P_{PV}(t) = MPPT\left(R(t), K(t)\right) \tag{1}$$

where *R(t)* and *K(t)* are the irradiation and temperature data, respectively.

3.7V-11.4Ah Li-ion cells are assumed. Charge/discharge operations are ordered by the central EMS module. The battery SOC changes accordingly to the amount of current, $I_{bat}(t)$,

$$SOC(t+1) = SOC(t) + \frac{I_{bat}(t)}{Ah_{Bat}} \tag{2}$$

where relation between SOC and OCV follows OCV-SOC table provided by the vendor. The maximum charge/discharge current and the range of state-of-charge (SOC) are limited as,

$$I_{bat\_min} \le I_{bat}(t) \le I_{bat\_max} \tag{3}$$

$$SOC_{min} \le SOC(t) \le SOC_{max} \tag{4}$$

Load consumption patterns are designed and a one-year profile is generated adding Gaussian white noise on the normal pattern. Grid electricity price greatly affects evaluation and optimization of the cost function. The paper assumes a varying pricing policy which encourages night-time electricity usage: 60 won for night-time, 128 won for middle-peak period, 180 won for high-peak period [24]. A (1×24) vector c_{elec} represents daily varying electricity cost.

3. Energy Management System

EMS problem is an optimization process. A cost function is defined as below.

$$J = J_1 + J_2 \tag{5}$$

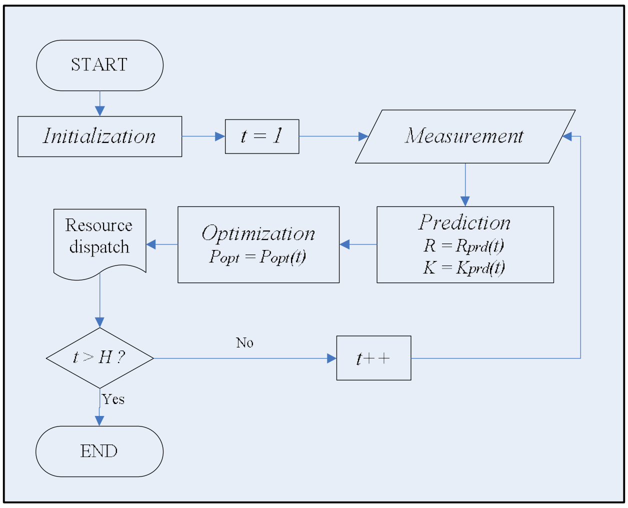

Fig. 2. Overall flowchart of the EMS scheme

where J_1 is electricity consumption in terms of its price, and J_2 is a weighted cost of charge/discharge operation of the battery. The proposed method is designed to minimize the cost function. The overall flowchart of the proposed approach is described in Fig. 2. The outer larger loop indicates the on-line execution running for total management period. The loop contains two smaller blocks, one is prediction stage and the other is optimization stage. After an optimal solution is derived, the EMS module dispatches the power resources between the elements. The specific methods of each stage are explained below.

A. Prediction stage: ARMA model

An example of prediction process at time *t* is described. Once a real data at time *t*, $R_{real}(t)$, is measured, auto-regressive (AR) model predicts the next $\hat{R}_{real}(t+1)$., that is,

$$\hat{R}_{real}(t+1) = -\sum_{i=1}^{p} a_i R(t-i) + w(t) \quad (8)$$

where $R_{real}(t)$is measurement at *t*, $\hat{R}_{real}(t+1)$ is prediction value, and $w(t)$ is white noise signal. The error between the current prediction vector and the reference vector is calculated,

$$e(t) = \left(R_{ref}(t) - R_{prd}(t)\right)/R_{prd}(t) \quad (9)$$

where $R_{prd}(t)$ is current prediction value on *t*-th data and $e(t)$ is error. This error is fed into the PI-controller which enables the current prediction data R_{prd} to follow the reference data.

$$u(t) = K_p e(t) + K_I \sum_{\tau=1}^{t} e(\tau) + 1 \quad (10)$$

$$R_{prd}(t+1,i) = R_{prd}(t,i)u(t) \quad (11)$$

where $u(t)$ is control variable, K_p is proportional gain, and K_I is integral gain of the controller. The control action is repeated with sampling interval of $T_s = 1/N_s$ until the new irradiation information is measured.

TABLE 1. OPERATING COSTS OF EMS's

Simulation interval	DP w/o prediction	On-line DP	Improvement
1st Jan. ~ 7th Jan.	94 9 M Won	85 1 M Won	10 3 %
1st April ~ 7th April	19.7 M Won	13.6 M Won	31.0 %
1st July ~ 7th July	36 9 M Won	31 9 M Won	13.4 %
1st Oct. ~ 7th Oct.	32.0 M Won	27.0 M Won	15.6 %

B. Optimization stage: Dynamic programming

The SOC level of the battery is used as the main variable in this DP problem. To get a DP solution, the algorithm examine all optimal values for every possible SOC variation from $t = 1 \ldots T$, where T is final time. For every SOC variation, the battery power is calculated, and the power flow between the microgrid and the grid is calculated,

$$P_{bat}(t+1) = -(SOC(t+1) - SOC(t)) \cdot P_{bat\_rating} \quad (13)$$

$$P_{grid}(t) = P_{load}(t) - P_{PV}(t) - P_{bat}(t) \quad (14)$$

The cost is obtained by pre-defined cost function in (5). After all the elements of cost matrix are acquired, the final SOC trajectory with lowest cost is chosen, and the optimal solution is completed.

4. Results

The algorithm composed of the prediction and the optimization parts is implemented and simulated using MATLAB/Simulink. Table.1 lists the costs of the proposed EMS and EMS without prediction for different simulation intervals. The proposed method has resulted in 10~30% of cost reduction compared to the DP-based scheme without prediction.

5. Conclusion

A distributed micro-grid system has been configure and modeled, as the object of EMS. DP based EMS is implemented on-line, while the strategies are improved backed up by prediction stage. ARMA model based forecasting has been exploited to give the constraints for every optimization execution. More precise forecasting method and verification of the scheme on hardware are left for future works.

Reference

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