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Real-time Battery Energy Management for Residential Solar Power System

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Abstract: An energy storage system is a key element of renewable-based power generation. Its flexible operational capabilities reduce not only the impact of intermittent power generation but also operational costs. In this paper, a dynamic penalty function is proposed to the charging term of the cost function to efficiently manage the battery energy and thereby reducing operational costs. The charging/discharging periods of the battery are effectively controlled based on the solar power generation and residential real-time electricity prices (RRTP). The optimisation problem formulated for the application of real-time energy management is solved with the help of particle swarm optimisation (PSO). It is shown that the proposed cost function can reduce operational costs over a time horizon of 96 hours by 4.2 per cent as compared to the cost function reported in the literature. Simulation studies are carried out to demonstrate the effectiveness of the proposed cost function over the existing cost function.

Keywords: renewable energy sources, optimum battery control, real-time energy management, particle swarm optimisation

1. INTRODUCTION

Due to increased concern about the energy crisis, rising electricity prices and environmental issues, the power generation sources are shifting from fossil fuels to renewable sources Hossain et al. (2018, 2017a,b). Among the renewable sources, the rooftop solar power has remarkably increased due to its flexible installation around the home environment with less maintenance costs. The typical home being connected to the grid, the power generated from the solar panels can be supplied to the grid utility depending on electricity prices. Although the electricity price per kWh is generally fixed, it may vary over time to have better demand management with the help of smart meter technologies capable of measuring power generation and demand in each time instant Li et al. (2017).

Power generation from solar panels is irregular in nature due to its dependence on solar irradiation and weather patterns, resulting in inconstant generation. To overcome this barrier and optimise electricity usages of the solar panels, an energy storage system (ESS), such as a battery, is often installed at house premises. The energy management unit is responsible for efficient power management with the help of an ESS Hossain et al. (2019a). An ESS absorbs surplus power and then dispatches it later when input sources are not available, e.g., at nighttime for solar panels. In addition, energy can be stored when electricity prices are low and sold during the hours of high prices to reduce operational costs, allowing more flexible and reliable energy management for a residential power system Hossain et al. (2019b).

To optimally control the battery energy for the reduction of electricity costs of investors, the formulation of a cost function considering charging and discharging factors needs to be carefully analysed in addition to the application of efficient algorithms. Although conventionally if-else rule-based policies, where initial sets of rules are fixed for different scenarios, are employed, they cannot provide an optimal control policy Venayagamoorthy et al. (2016); Wei et al. (2017a). Generally, in this method, energy is dispatched based on available power and state of charge (SOC) of the battery, and stored if power generation is higher than power demand Henze and Dodier (2002). In addition, abrupt charging and discharging decisions can decrease the lifetime of the storage system without providing maximum benefits.

To improve optimal control approaches for the battery energy, many optimisation algorithms, such as linear programming De Angelis et al. (2013); Luna et al. (2015); Hernández et al. (2017), dynamic programming Choi and Kim (2016), fuzzy logic Chaouachi et al. (2013) and adaptive dynamic control Wei et al. (2017b), are studied in the literature. In Teleke et al. (2010), an expert-based control approach incorporating operating constraints, such as SOC limits and charging/discharging current limits, is presented to optimally use the storage systems for dispatching renewable energy sources (RESs) smoothly. A power management mechanism using dynamic programming for photovoltaic (PV) systems with storage to allow massive penetration of PV power into a distribution network is described in Riffonneau et al. (2011). Adaptive dynamic programming (ADP) for the residential power manage-

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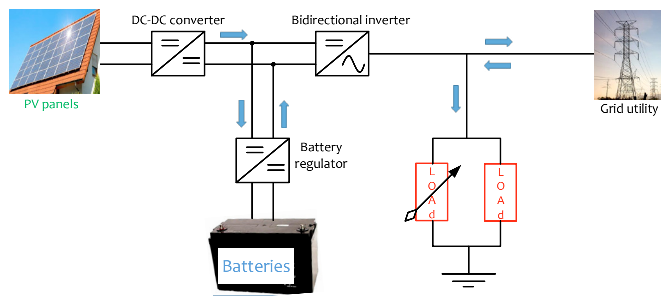


Fig. 1. A typical residential solar power system.

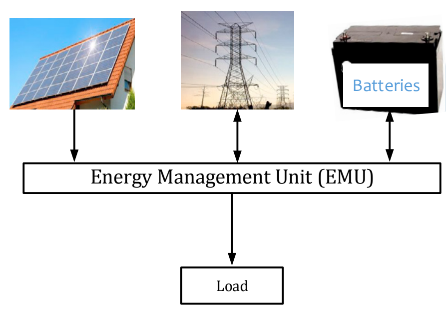


Fig. 2. Energy management unit for a residential PV system.

ment and control that focus on home battery management is applied in Huang and Liu (2011). ADP is employed in an office building to optimally control battery energy Shi et al. (2017). A comparative study based on the costs of a residential energy management by using action dependant hierarchical dynamic programming (ADHDP) and particle swarm optimisation (PSO) techniques is developed in Fuselli et al. (2012).

Although the formulation of an objective function has direct involvement in altering results, little attention has been paid in the literature when applying it to efficiently control the battery energy. To find the optimal charging and discharging amounts for exchanging energy with the grid utility depending on electricity prices and availability of the solar panels, this paper proposes a cost function in which a penalty function related to dynamic electricity prices is integrated with the charging component. In the cost function, the penalty function adds an extra value to the charging component to forcefully charge the battery during the low electricity prices. The cost function is solved using a PSO that runs any time a new sample is available (in our simulations this occurs with a sampling time equal to 1 hour).

The rest of the paper is organised as follows. Section 2 introduces an overview of a residential power system. In Section 3, different components of a residential power system to facilitate the analysis are modelled. Section 4 proposes a cost function with constraints. Simulation results are performed in Section 5. Section 6 concludes the study.

2. DESCRIPTION OF RESIDENTIAL PV SYSTEM

It is assumed that a house connected to the grid utility is equipped with a solar panel and a battery to meet its power demand as shown in Figure 1. Both the grid and solar panel can supply the power to the loads and/or charge the battery. The excess energy from the panel can be sold to the grid in order to decrease electricity cost. In this study, the battery energy is not sold due to the concern of security and reliability of continuous power supply. The energy management unit (EMU), shown in Figure 2, manages the energy to assure power balance criteria of the house over the time periods through power exchange programs with the grid during the excess and scarcity of solar power generation. The total capacities of the photovoltaic (PV) generator and battery are taken as 4 kW and 6 kWh, respectively. Battery capacity is considered to supply power demand for three hours. The parameters of a solar generator and battery are given in Table 1.

As the solar panel is operated in the maximum power point tracking (MPPT) modes to extract maximum power due to shortening payback periods, controlling battery power dispatch is the only option for the power management. The battery can be used by one of the following options at a time:

- Charge modes: the battery can be charged from the grid and/or solar power with an energy quantity which is not beyond the charging rate;
- Discharge modes: the battery supplies energy to the loads when prices are high with an energy quantity within the battery discharging rate;
- Inactive modes: there is no activity of the battery energy in this mode as the grid utility directly supplies electricity to loads at certain hours in order to consider economic perspectives.

Table 1. Input parameters.

Parameter	Value	Unit
PV generators		
Total covered area, A	25	m^2
Efficiency, η_s	18	%
Maximum power	4	kW
Battery		
Initial energy level, BL_o	3	kWh
Maximum energy level, BL_{max}	6	kWh
Minimum energy level, BL_{min}	1.2	kWh
Energy capacity	6	kWh
Maximum charging rate	0.6	kWh
Maximum discharging rate	-0.6	kWh

3. SYSTEM MODELING

3.1 Solar generators

In solar power generation, the size of PV panels and solar irradiation (SI) play a vital role. SI, which decides the amount of direct and defused energy on an earth surface, varies from place to place and is expressed as kW/m^2. The PV panels are operated in the MPPT mode to use maximum energy.

The output power of the solar panel relies on its size and efficiency, and can be measured as a function of SI with the assumption of operation at MPPT mode as follows Hossain et al. (2019c):

$$P_s = \eta_s * A * SI(1 - 0.005(t_o - 25)) \tag{1}$$

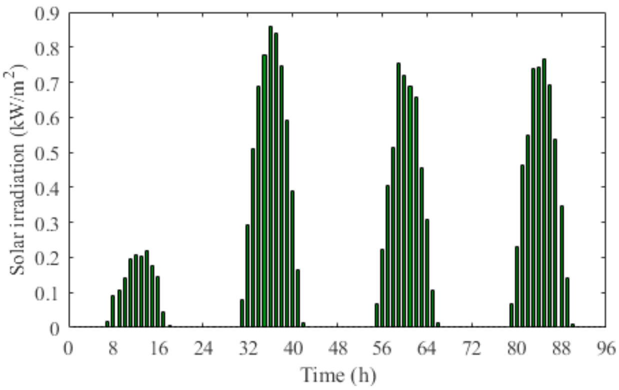


Fig. 3. Solar irradiation over a 96 h horizon.

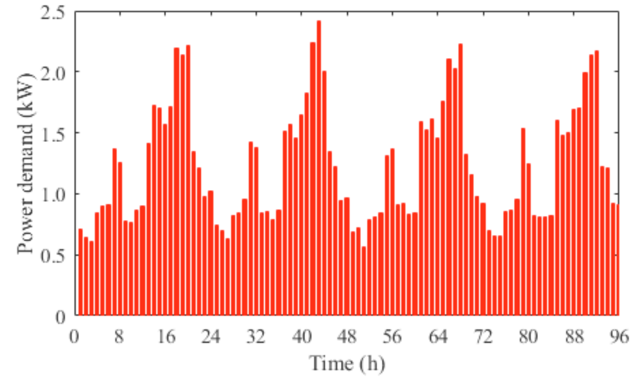


Fig. 4. Power demand of a householder over a time horizon of 96 hours.

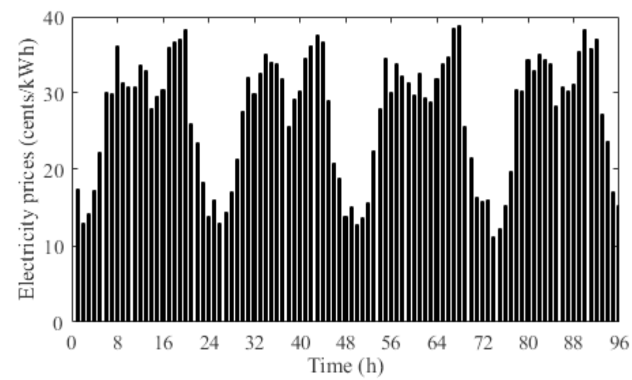


Fig. 5. Real-time electricity pricing in a 96 h horizon.

where η_s and A are the overall efficiency and area of PV panels, respectively, SI and t_o denote solar irradiation and outside air temperature, respectively.

3.2 Converters

One of the main purposes of a converter, including dc/dc and dc/ac conversion, is to match the frequency of the power generated by solar panels to the grid utility. This is done by converting from dc power to ac power. Thus, converters' efficiency is considered as follows Borhanazad et al. (2014); Darras et al. (2010):

$$\eta_{con} = \frac{\frac{P_s}{P_n}}{\frac{P_s}{P_n} + \eta_o + k(\frac{P_s}{P_n})^2} \tag{2}$$

where $\eta_o = (\frac{10}{\eta_{10}} - \frac{1}{\eta_{100}} - 9)/99$ and $k = \frac{1}{\eta_{100} - \eta_o - 1}$. P_n and P_s are the nominal power and output power of the converter, respectively, and η_{100} and η_{10} are the converter efficiency provided by manufacturer at 100% and 10% nominal power, respectively.

3.3 Storage systems

The installation of the storage system can increase profits from a solar system by charging and discharging power depending on the electricity prices. The charging and discharging models of the battery can be represented as follows:

$$BL(t) = BL(t-1) + \Delta t P_c(t)\eta_c \quad \text{if battery is charged} \tag{3}$$

$$BL(t) = BL(t-1) + \Delta t P_d(t)/\eta_d \quad \text{if battery is discharged} \tag{4}$$

subject to the following battery constraints:
Power limits:

$$P_{c,max} > P_c > 0$$
$$P_{d,max} < P_d < 0$$

Battery energy level limits:

$$BL_{max} > BL(t) > BL_{min}$$

where $P_c(t)$ and $P_d(t)$ are the charging and discharging powers of the battery at time, t, respectively, $BL(t)$ and Δt are the battery energy level at time t and the interval of time period, respectively, and η_c and η_d are the charging and discharging efficiency, respectively. For simplicity, η_c and η_d are assumed as unity.

The operating commands, $u(t)$, of the battery from the optimisation algorithm determine charging and discharging energy amounts. The positive values of $u(t)$ indicate $P_c(t)$ while negative values refer to $P_d(t)$.

3.4 Loads

The residential load, which fluctuates hourly with noise, $L(t)$, is a (piecewise) continuous function with the time step of 1 h as chosen in Fuselli et al. (2013); Liu et al. (2018). The load profile of which maximum load is around 2.5 kW for a house is illustrated in Figure 4. It is observed that every day there is physical-activity routines of the householders reflected as a spike during the day time and the highest activities are carried out during the night-time, revealing cooking and relaxing activities before the sleeping time.

3.5 Electricity price of the grid

One of the main features of the residential solar system is to exchange power with the grid utility depending on electricity prices. For simplicity, the residential real-time electricity prices (RRTP) for buying and selling electricity at time t is assumed identical, denoted as $C(t)$ (cents/kWh). In real-time pricing, the rate varies over the time periods depending on wholesale market prices that are changed according to the power demand, i.e., peak demand indicates a high rate of electricity usages Huang and Liu (2011). A typical real-time electricity rate is demonstrated in Figure 5. The unit of the rate is expressed as cents of an Australian dollar per kilo-watt hour. The rates are set to be suitably matched with the future Australian electricity market, although the fluctuation is adopted from the real-time electricity prices Ref (2018).

4. THE PROPOSED COST FUNCTION

The aim of this study is to minimise electricity cost by the optimal control of battery energy. In this case, the cost function is first formulated then the PSO algorithm is applied in order to determine the optimal control operations of an ESS.

The minimum values of the cost function refer to the lowest energy costs with optimal control policies. The cost function used in Squartini et al. (2013); Gudi et al. (2012); Fuselli et al. (2013) to charge the battery from renewable energy for obtaining optimal control actions of the battery is given as follows:

$$Cost(t) = \sqrt{(\zeta_1(t)(C(t)/C_{min}))^2 + \zeta_2(t)^2} \tag{5}$$

where
$\zeta_1(t) = L(t) - P_{sT}(t) + u(t)$,
$\zeta_2(t) = BL_{max} - (BL + u(t))$,
and where $L(t), P_{sT}(t)$ and $u(t)$ denote loads, total solar power and battery commands at time t, respectively. The first term of Eq. (5) indicates a discharging component of the battery energy, while the second term is a charging parameter. A charging component is a critical portion for the optimal controls of the battery energy. This is because of its involvement in charging the battery during low electricity prices and the full battery charging during an upcoming event. As a result, a dynamic penalty function is proposed for the first time in this paper to complete the task in an optimal way as follows:

$$Cost_{ppd}(t) = \sqrt{(\zeta_1(t)C(t))^2 + (f_{pc}(C)\zeta_2(t))^2} \tag{6}$$

where $f_{pc}(C) = k - C(t)$ refers to a penalty function for the optimal charging of the battery energy determining k value. Changing the value of k, which is 35 in this study, has a direct effect in reducing electricity costs. The minimum values of the $Cost_{ppd}$ indicate discharging the battery during low power generation and higher electricity prices, or charging the battery when power generation is high and prices are low. The command signals, u, must satisfy the battery constraints to protect premature degradation of the battery capacity, otherwise the command is invalid and must be discarded with a high penalty cost during the optimisation process. As the cost function is calculated with a time step of 1 hour (step-by-step), the algorithm assesses the function as an on-line approach.

4.1 Constraints:

The following constraints to determine the feasible solutions of the cost functions are imposed as follows:

Energy balance: The cost function must satisfy the energy balance equation as follows:

$$P_g(t) + P_{sT}(t) = L(t) + u(t). \tag{7}$$

The u is placed at the right-hand side of the equation as the positive values indicate charging similar to a load characteristic.

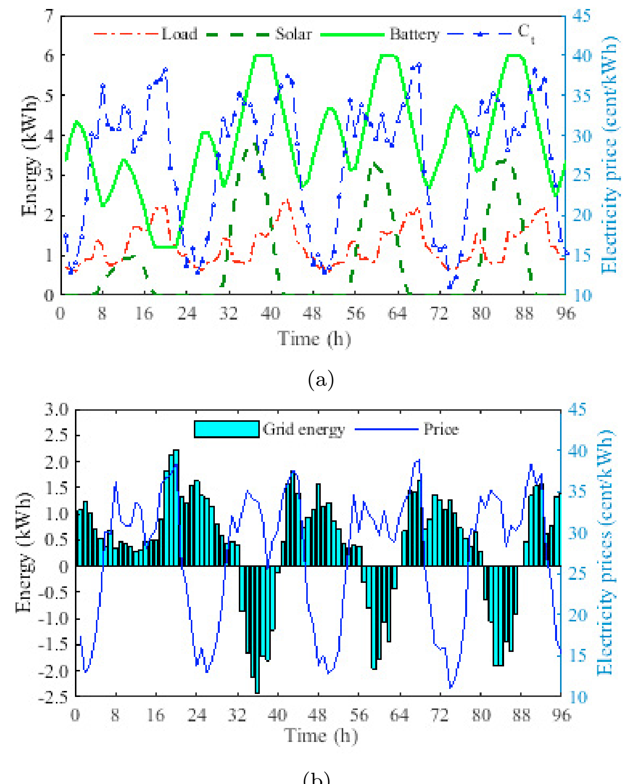


Fig. 6. Existing cost function: (a) charging/discharging cycles of the battery energy and (b) energy exchange with the grid.

Battery energy: The commanded signals, $u(t)$, control the battery energy as an on-line approach since the cost function proceeds step by step over the time horizon without the prior knowledge of the energy status. The values of $u(t)$ must satisfy the following constraints in order to extend the lifetime and efficiency of a battery.

1) The charging and discharging rate must be within the given limitations, i.e., $P_{d,max} < u(t) < P_{c,max}$.

2) The energy level of the battery must maintain upper and lower limits, i.e., $BL_{min} < BL(t) + u(t) < BL_{max}$.

5. SIMULATION RESULTS

This paper considers an EMU unit which manages the energy flow of the sources to ensure continuous power supply to the houses while reducing electricity costs. Electricity cost is reduced by optimal battery operations as a function of power generation, load demand and electricity prices, with the application of the PSO algorithm. Battery capacity is chosen as 6 kWh, and the lower and upper storage limits are considered as 1.2 kWh and 6 kWh, respectively. The initial energy level of the battery is taken as 3 kWh. Table 1 displays the input values of the residential solar system. The simulation is calculated over 96 hours horizon with a time slot of 1 h.

Table 2. Comparisons of cost functions.

Cost function	Electricity cost	% Saving
Existing (5)	8.06	0
Proposed (6)	7.72	4.2

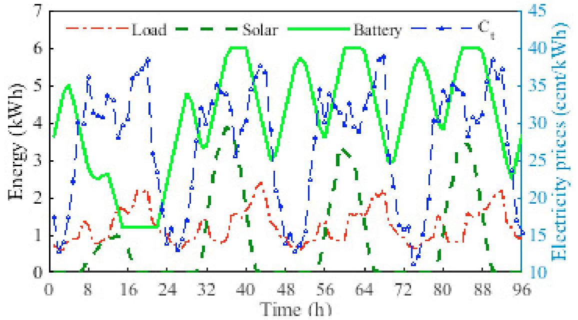
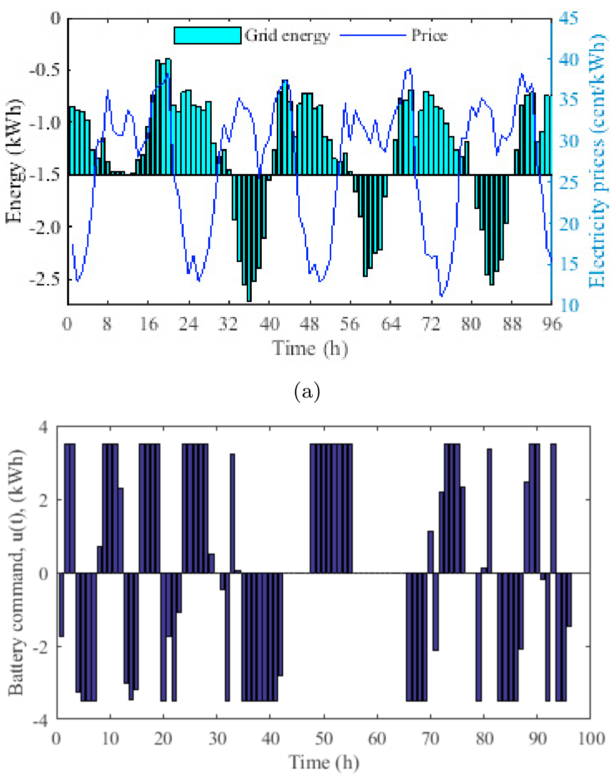


Fig. 7. Proposed cost function: optimal charging/discharging cycles of the battery energy.



(a)

(b)

Fig. 8. Proposed cost function for Scenario 1: (a) energy exchange with the grid and (b) command signals for the battery energy.

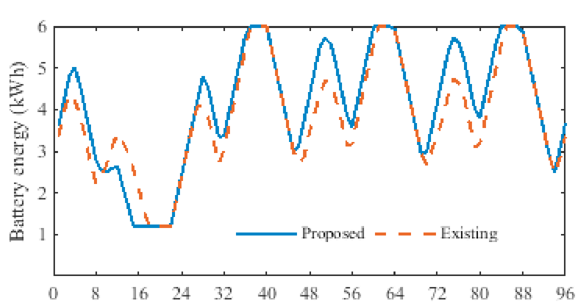


Fig. 9. Comparison between the proposed and existing cost functions.

5.1 *The existing cost function*

The cost function reported in Squartini et al. (2013); Fuselli et al. (2013) is formulated to charge the battery from the solar power and grid utility supply, and discharge it when power demand is greater than power generation. The charging term that corresponds to the absence of the full charge incurs an extra cost. The simulation results are shown in Figure 6. The battery is charged during the low electricity prices up to a certain time, $t = 4.35$ h, and the power demand is fulfilled from the grid utility simultaneously. After that, the battery discharges the power for feeding the loads to decrease the electricity costs due to high electricity prices. It is also observed that the battery is charged during higher renewable power than the load demand. In the cost function, the algorithm endeavours to provide an optimal solution; however, it struggles to find the solution due to the lack of a proper formulation. The electricity cost of this method is A\$8.06 for a time horizon of 96 hours.

5.2 *The proposed cost function*

The result from the cost function proposed is demonstrated in Figures 7 and 8. It is observed that the charging and discharging cycles of the battery are similar to the alternative function, but with reduced operational costs as A\$7.72 for a time horizon of 96 hours. It can be seen from Figure 7 that the storage system discharges its energy to the lowest energy level at time $t = 15$ h, and after that the battery has no activities up to time $t = 22$ h due to the lack of the solar power and high cost involvement in charging the battery. Similarly, the battery reaches the height energy level at time $t = 37$ h, and the battery is in an inactive mode until $t = 40$ h due to higher power generation from the solar panels than the power demand. In this time period, the solar power is supplied to the grid to earn profit. The charging/discharging commands of the battery are illustrated in Figure 8b. It should be pointed out that the formulation takes into account the use of the battery energy to send power to loads when power generation is less than the power demand instead of selling power to the grid utility during high electricity prices. A comparative study between the cost functions is shown in Figure 9 and their relative electricity costs for a four days of estimation is tabulated in Table 2.

6. CONCLUSION

The rising electricity prices and environmental concerns are the driving force of electricity customers for adopting solar panels on their rooftop with an ESS to combat the adverse situations. However, the lack of a proper cost function formulation can reduce the efficient use of the battery energy. This paper proposes a cost function in which a penalty function integrated with the charging component of the function is used to efficiently manage the battery energy by the control of charging/discharging behaviours. PSO algorithm is applied to facilitate the analysis of the cost functions reported in the literature and the one proposed here. It is observed that the proposed cost function reduces electricity costs of a house equipped with solar panels and a battery by around 4.2 per cent from the existing cost function over a time horizon of 96 hours. Numerical results and comparisons are carried out to exhibit the effectiveness of the proposed function, and it can be concluded that the performance of the proposed cost function is superior to the existing function.

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