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전기자동차 배터리를 활용한 공장의 에너지 관리 방안 제안+

(Proposal of a Factory Energy Management Method Using Electric Vehicle Batteries)

박 남 기[1)], 이 석 주[2)], 고 병 수[3)], 딘 민 차 우[4)], 이 준 엽[5)], 박 민 원[6)*]
(Nam-Gi Park, Seok-Ju Lee, Byeong-Soo Go, Minh-Chau Dinh, Jun-Yeop Lee, and Minwon Park)

요 약 공장의 에너지 효율을 높이는 방안 중 공정 스케줄링은 제조 공정에서 자원을 최적으로 할당하여 제품의 생산 계획을 수립하는 활동이다. 그러나 야간 근로가 불가피한 경우에는 이러한 전략이 효과적으로 적용되지 않을 수 있다. 또한, 생산 요구량의 지속적인 변화로 인해 실제 공장에서의 적용에 어려움이 있다. 최근에는 전기자동차의 보급이 급증함에 따라 전기자동차 배터리를 에너지 저장 시스템으로 활용하는 기술이 주목을 받고 있다. 이러한 배터리를 활용한 기술은 공장 에너지 관리를 위한 대안이 될 수 있다. 본 논문에서는 전기자동차 배터리를 활용한 공장 에너지 관리 방안을 제안한다. 제안된 방안은 전기자동차 배터리 충전 상태 및 TOU(Time-of-use)를 고려하여 PSCAD/EMTDC 소프트웨어에서 분석된다. 제안된 방안은 예측된 전력 사용량과 TOU를 고려하여 수립된 공정 스케줄링과 비교 분석된다. 결과적으로 공정 스케줄링은 하루에 4,152원, 제안된 방안은 7,286원의 전기 요금을 절감하였다. 본 논문을 통해 공장 에너지 관리를 위해 전기자동차 배터리 활용 가능성을 확인할 수 있었다.

핵심주제어: 공장 에너지 관리, 전기 자동차 배터리, PSCAD/EMTDC

Abstract Increasing energy efficiency in factories is an activity aimed at optimizing resource allocation in manufacturing processes to establish production plans. However, this strategy may not apply effectively when night shifts are unavoidable. Additionally, continuous fluctuations in production requirements pose challenges for its implementation in the factory. Recently, with the rapid proliferation of electric vehicles (EVs), technology utilizing electric vehicle batteries as energy storage systems has gained attention. Technology using these batteries can be an alternative for factory energy management. In this paper, a factory energy management method using EV batteries is proposed. The proposed method is analyzed using PSCAD/EMTDC software, considering the state of charge of EV batteries and Time-of-Use (TOU) rates. The proposed method was compared with production scheduling established considering predicted power usage and TOU rates. As a result, production scheduling saved 4,152 KRW per day, while the proposed method saved 7,286 KRW in electricity costs. Through this paper, the possibility of utilizing EV batteries for factory energy management has been demonstrated.

Keywords: Factory energy management, EV battery, PSCAD/EMTDC

* Corresponding Author: capta.paper@gmail.com
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1) 국립창원대학교 전기공학과, 제1저자
2) 국립창원대학교 메카트로닉스연구원, 제2저자
3) 국립창원대학교 메카트로닉스연구원, 제3저자
4) 국립창원대학교 메카트로닉스연구원, 제4저자
5) 국립창원대학교 전기공학과, 제5저자
6) 국립창원대학교 전기공학과, 교신저자

1. Introduction

As industrial electricity demand rapidly increases, the reduction of energy consumption and the enhancement of energy efficiency in factories have become key objectives for modern industries. Production scheduling entails the allocation of limited resources to tasks based on time criteria. This schedule delineates the start and completion dates of each stage of the production process and its corresponding tasks, to maximize production efficiency. Considering dynamic prices, production scheduling can offer a strategy for conducting activities during off-peak hours, such as evenings or nights, to circumvent high electricity rates during the day. However, applying it in real factories is difficult due to continuously changing production requirements, changes in production lines, and difficulties in understanding material inventory, so an alternative is required.

The demand for electric vehicles (EVs) has been increasing due to environmental regulations due to global warming and advances in battery technology. As demand for EV increases, vehicle-to-grid (V2G), a technology that uses EV batteries as ESSs or distributed power sources, is receiving attention. V2G technology connects the EV battery to the power grid and reversely transmits electricity from the vehicle to the power grid. In addition to V2G, technologies using EV batteries can be classified into vehicle-to-home, and vehicle-to-building depending on the scope and target of the application (Liu et al., 2013; Sousa et al., 2018; Mahmud et al., 2018; Pearre and Ribberlink, 2019; Vadi et al., 2019). Using EV batteries as ESSs in factories can expect cost-effective energy management technologies.

In this paper, a method using EV batteries owned by workers for factory energy management was proposed. The proposed method analyzes the possibility of factory energy management compared to production scheduling used for conventional factory energy management.

First, this paper designed a power consumption prediction model using a long-short-term memory (LSTM) for production scheduling. The production scheduling considering the power consumption prediction model and time-of-use (TOU) was analyzed. A method using the EV batteries of workers for factory energy management based on TOU and state of charge (SOC) of EV batteries was proposed. EV batteries, typical 3.3 kW bi-directional chargers, and factory load are modeled using PSCAD/EMTDC. The proposed method is integrated with the charge and discharge controller of bi-directional chargers. The electricity rates saved in the factory through production scheduling and the proposed method were calculated based on TOU, respectively.

As a result, the production scheduling shifted the main production time from the peak period to the mid-peak or off-peak period. The factory saved 4,152 KRW per day on electricity rates. The proposed method saved 7,286 KRW per day on electricity rates. For this method to be successfully applied, the factory must provide economic rewards to EV owners for the cost between the TOU rate applied to the factory during peak hours and the TOU rates applied to the EVs charging during off-peak hours. This paper is a conceptual paper that involves EVs in factory energy management and is expected to be able to manage factory energy more efficiently.

2. Analysis of a production scheduling

Production scheduling is a method to improve energy efficiency in factories by allocating limited resources to tasks based on time criteria.

This schedule specifies the start and end dates for each stage of the production process and its associated tasks, aiming to maximize production efficiency. By considering dynamic pricing, production scheduling can provide a strategy for conducting operations during off-peak hours, such as evenings or nights, to avoid high electricity rates during the daytime.

In this paper, the production scheduling was implemented considering the predicted power consumption data for each facility and the TOU rates.

2.1 Design of the power consumption prediction model using LSTM

In the domain of energy consumption prediction, data has a strong periodic. For example, the peak period of electricity usage in the day occurs at certain fixed times, and it also shows another periodicity that changes depending on the season and month (Wang et al., 2020). Therefore, an approach that can accurately find the periodicity of time series data is needed. A recurrent neural network (RNN) architecture considering the sequential aspect of input data and the notion of time is the most popular model for time series prediction (Lee et al., 2020; Ngo et al., 2023; Lee et al., 2024). However, RNNs have the disadvantage of not being able to connect information when the gap between input data is large. To overcome this limitation of RNNs, the LSTM architecture was proposed. (Amalou et al., 2022).

The design process for the LSTM model for the power consumption prediction is the collection of data, preprocessing, parameter selection and tuning, and training. The accuracy of the LSTM model was evaluated using symmetric mean absolute percentage error (SMAPE). Out of a total of 10,571 power consumption data collected at 15-minute intervals through the factory energy management system (FEMS), 8,164 data were used for learning, and the remaining data were used for verification. To predict power consumption having daily and weekly periodicity, 672 past data from at least one week prior were input.

Table 1 Specifications of the LSTM model

Parameter	Value
Number of inputs	672
Number of outputs	1
Number of hidden layers	2
Number of neurons in hidden layer 1	128
Number of neurons in hidden layer 2	256
Activation function in hidden layers	Sigmoid, Tanh
Activation function in the output layer	Linear
Adapting learning function	Adam
Learning rate	0.001
Loss function	MAE
Accuracy metrics	MAE, SMAPE

Table 1 represents the specifications of the LSTM model based on the design process. Fig. 1 shows the predicted results obtained by inputting data of one facility for a randomly selected week, and the SMAPE of the LSTM model achieved 93.6%.

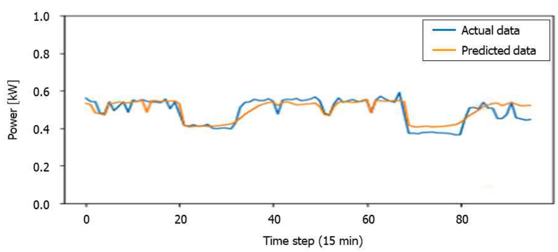

Fig. 1 Predicted results of the power consumption for one facility

2.2 Design of the production scheduling

The production scheduling was designed considering the power consumption prediction and the TOU rates introduced by the Korea Electric Power Corporation (KEPCO). TOU rates vary depending on the season, but peak and off-peak times of the day are the same depending on the season. In this paper, the industrial rates for the summer season were selected, and the results can be derived using the same principle for the remaining seasons, with only different rates.

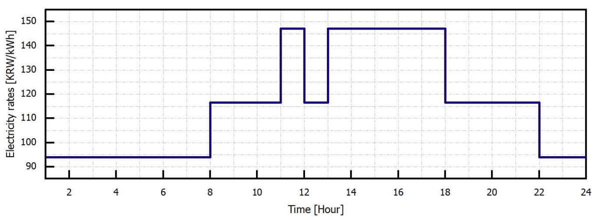

Fig. 2 Industrial electricity rates in the summer season based the TOU

The object of production scheduling is to reduce electricity rates by shifting the main production time of the factory from the peak period to the off-peak period. A linear programming method is employed to derive facility operating conditions that minimize energy costs The energy cost function is a linear function consisting of the linear relationship of the input data, the operation of the facility (ON/OFF), and the TOU rates. The energy cost function of the factory for implementing production scheduling can be expressed as follows:

$$T_{cost} = \sum_{t=0}^{T}\sum_{n=1}^{N}((\rho_{n,t} \times P_n) \times EP_{1,t}) \qquad (1)$$

where, $\rho_{n,t}$, P_n, and $EP_{1,t}$ are operation of n facility, power consumption of n facility, and TOU rates, respectively. Fig. 3 shows the process for establishing production scheduling.

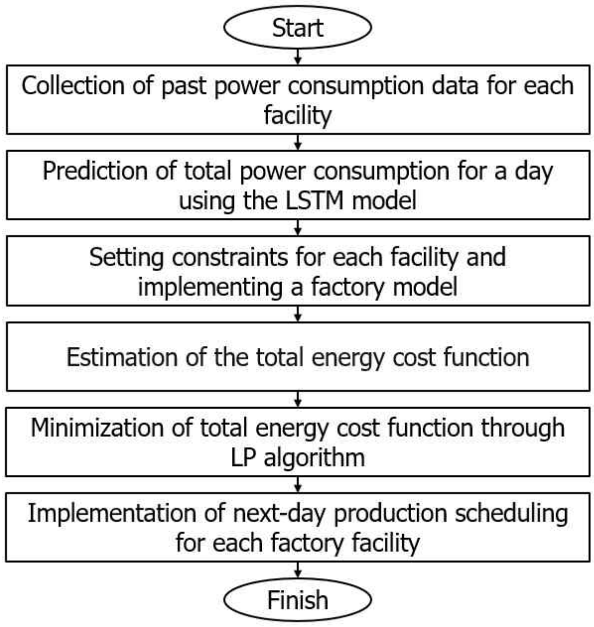

Fig. 3 Process for establishing production scheduling

Fig. 4 shows the power consumption of each facility before the establishment of production scheduling. The operation time was shifted from the main production hours of 13:00 to 18:00 to 18:00 to 23:00, as shown in Fig. 5. As a result of adjusting operations of each facility through the production scheduling, 4,152 KRW was saved per day. The production scheduling considering dynamic prices shifts the main production times from the peak period to the mid-peak or off-peak period.

Therefore, the production scheduling considering dynamic prices cannot be effectively applied to factories that operate only during the day. Moreover, a difficulty in general production scheduling is the continuously changing production requirements from the sales department. This reduces the concentration of production planners and forces them to establish production scheduling based on experience. Changes in the production

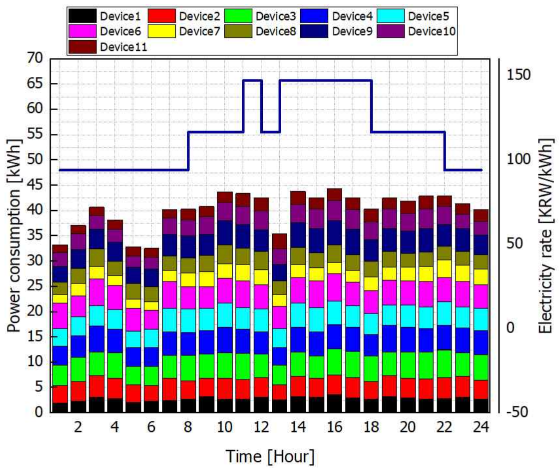

Fig. 4 Power consumption before the establishment of production scheduling

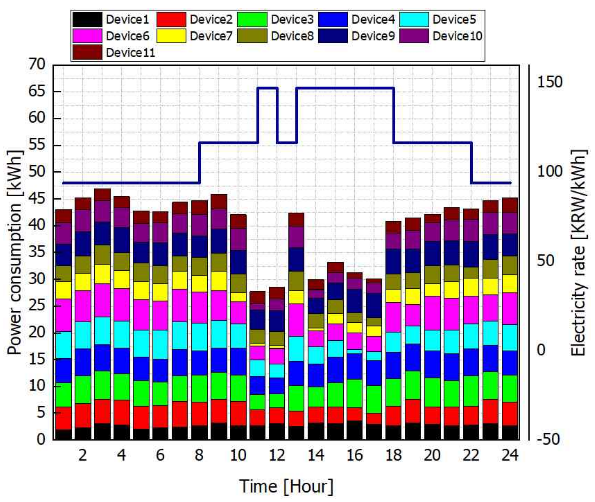

Fig. 5 Power consumption after the establishment of production scheduling

line and difficulty in determining the real-time status of material inventory are also factors that prevent production scheduling from being applied to real factories. As a result, a method is needed cost-effectively to improve energy efficiency in real factories.

3. The factory energy management method using EV batteries

The factory energy method using EV batteries is considered TOU and SOC. When an EV is connected to a charging station inside the factory, FEMS requests SOC information on the EV battery. FEMS can control the charging and discharging of EV batteries connected to the charging station. Additionally, FEMS requests the quality and price of electricity from the electric utility to calculate electricity rates based on the TOU. FEMS performs discharging of EV batteries based on the TOU and SOC information. The proposed method only considered the TOU and SOC of EV batteries. Fig. 6 shows a schematic diagram of the proposed method.

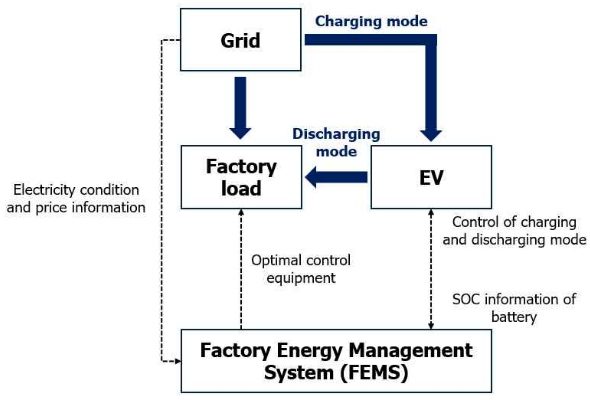

Fig. 6 Schematic diagram of the proposed method

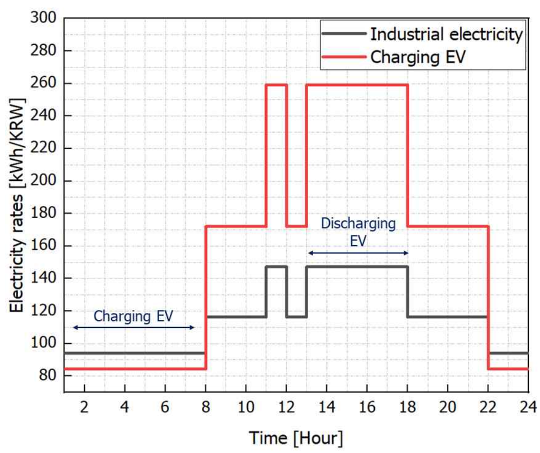

Fig. 7 TOU about industrial electricity and charging EV

3.1 Time of use

Fig. 7 shows industrial electricity rates and EV charging rates provided by KEPCO. The method using an EV battery is to charge the EV battery during the off-peak period when electricity rates are relatively low and discharge it through the bi-directional charger to manage the factory energy during the peak period.

3.2 SOC of EV battery

Fig. 8 shows the battery SOC of a typical commuter EV for factory energy management. The battery of EV was discharged to go to work in the morning and it can be fully charged during morning work. Fully charged EV batteries begin to discharge at 13:00, when electricity rates are highest, reducing the peak on the factory. Considering the EV owner's mobility, the battery's usable capacity range is limited to 40%. EV owners leave work with 40% of their battery capacity remaining and fully charge it with cheap electricity at night. In other words, the battery is only discharged to 40% from 13:00 to 18:00, when electricity rates are the highest and factory load is highest.

Fig. 9 shows the control algorithm of the bidirectional charger based on the proposed method. First, the proposed method's bidirectional

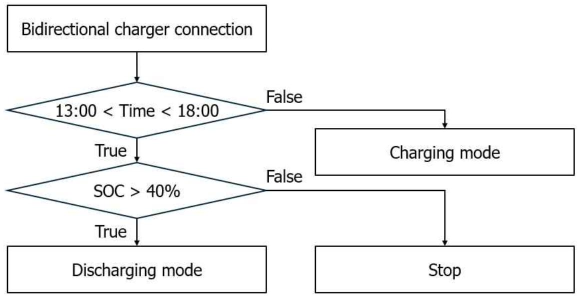

Fig. 9 Control algorithm of the bidirectional charger based on the proposed method

charger determines the charging and discharging modes according to time. Next, the battery SOC is received from the EVs and the discharge mode is determined when it is over 40%.

4. Analysis of factory energy management using EV batteries in PSCAD/EMTDC software

4.1 Modeling of the bi-directional battery charger using PSCAD/EMTDC

PSCAD/EMTDC simulation was performed to analyze the proposed method. The simulation model consists of the EV batteries, bi-directional battery chargers, and factory load as shown in Fig. 10. In this paper, lithium-ion batteries with high energy density and power density were

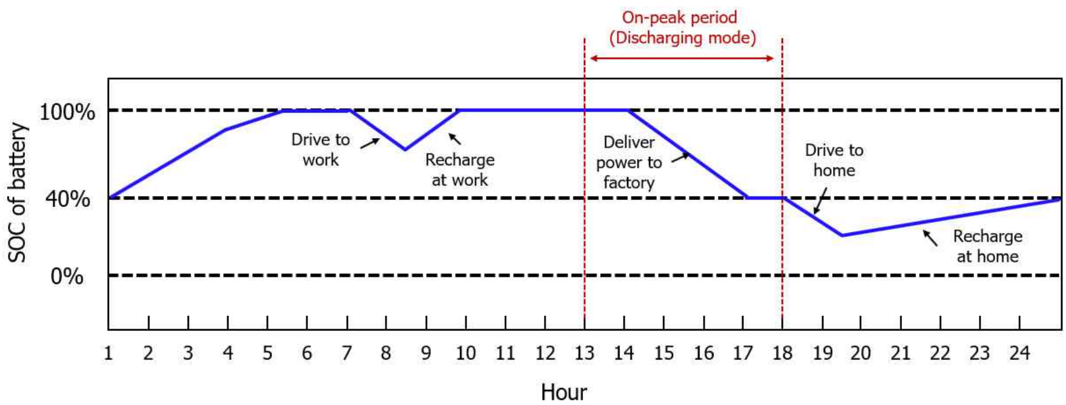

Fig. 8 Battery SOC of a typical commuter EV for factory energy management

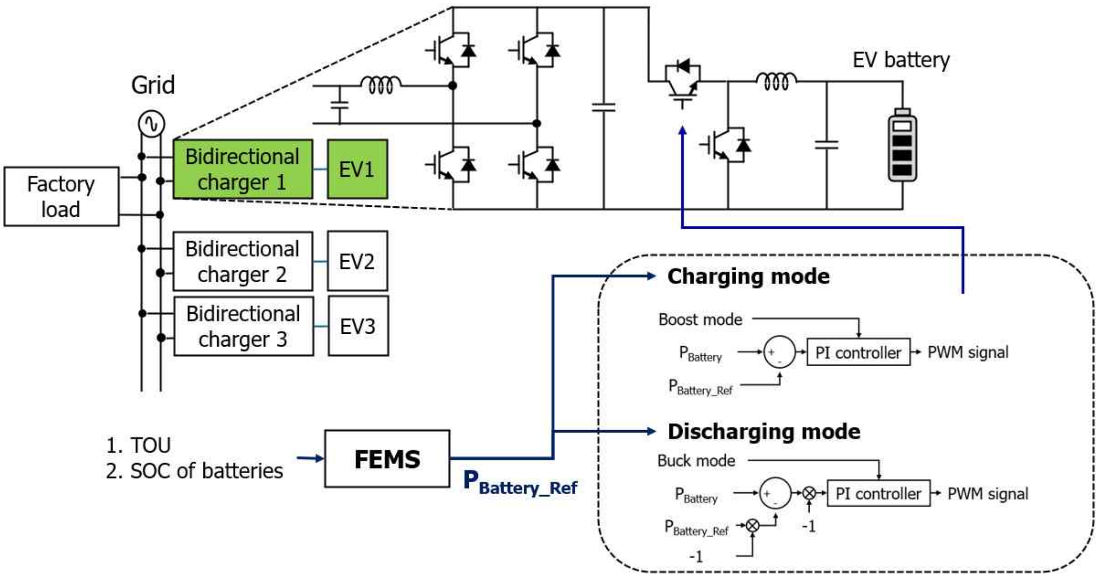

Fig. 10 The simulation model including typical topology for a single-phase bi-directional charger

selected among commercially available EV batteries (Tremblay et al., 2007). Table 2 represents the parameters of the selected lithium-ion battery considering the battery discharge curve. Currently, popular EV battery chargers allow a only one-way power flow for charging. Implementation of the proposed method requires an EV charger that allows bi-directional power flow between the factory and the EV battery.

Table 2 Parameters of the lithium-ion battery

Parameter	Value
Nominal voltage	330 V
Nominal capacity	50 Ah
Rated capacity	53.5 Ah
Fully charged voltage	380 V
Exponential voltage	360 V
Exponential current	4.5 Ah

The typical topology of a single-phase bi-directional charger consists of an AC/DC converter and a DC/DC converter (Himanshu et al., 2014). The AC/DC converter rectifies AC power to DC power during charging mode and DC power of the EV battery to AC power and, supplies it to the factory during discharging mode. The DC/DC connector controls bi-directional power flow, as a buck converter during charging mode or a boost converter during discharging mode. Table 3 represnets the parameters of a 3.3 kW bi-directional battery charger.

Table 3 Parameters of a 3.3 kW bi-directional battery charger

Parameter	Value
Rated power	3.3 kW
AC grid voltage	220 V
DC bus voltage	350 V
DC link capacitance	4,400 μF
Filter inductance	3 mH
Filter capacitance	4 μF
Switching frequency	10,000 Hz

The factory load from 13:00 to 18:00 was modeled using a variable resistor.

4.2 Simulation results of EV batteries discharging for factory energymanagement

For the simulation, 3 EVs with 100% SOC of battery are assumed to be connected to bi-directional chargers. FEMS commands a discharge of 3 EVs starting at 13:00 when peak rates begin to apply. And unless the battery SOC reaches 40%, the EV battery continues to discharge until 18:00. If the SOC of battery reaches 40% during the discharge mode, it remains at 40%.

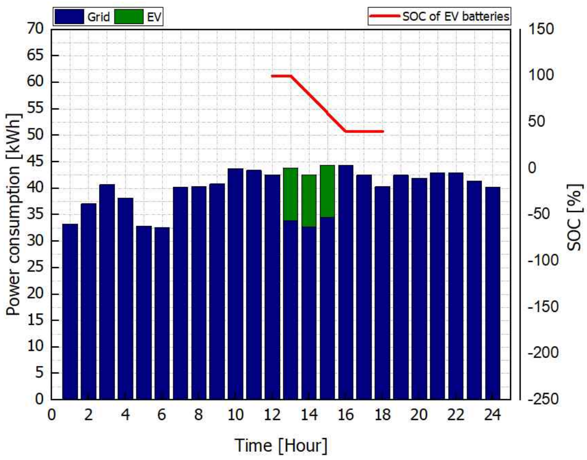

Fig. 11 Simulation result of EV batteries discharging during peak periods

Fig. 11 shows the simulation result when 3 EVs were discharged from 13:00. The 3 EV batteries discharged approximately 9.9 kWh per hour. The 3 EV batteries were discharged for 3 hours from 13:00 to 16:00. The electricity rates of factory were reduced by 7,286 KRW per day by applying the electricity rates during peak hours. Table 4 shows a comparison between the proposed method and production scheduling.

Fig. 12 shows the simulation result when EV batteries have different SOCs. At 13:00, the SOC

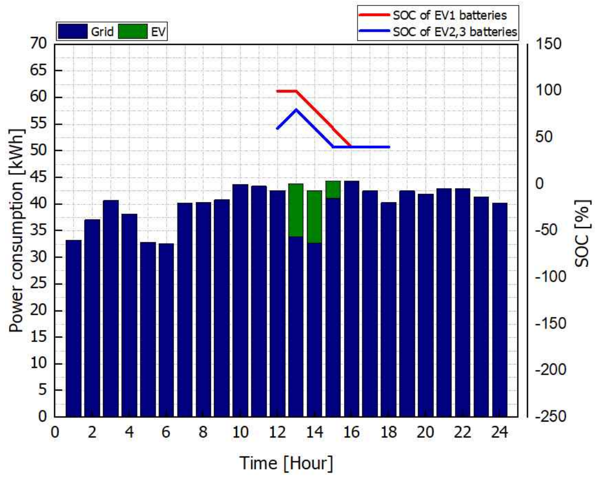

Fig. 12 Simulation result when EV batteries have different SOCs.

of the battery of EV 1 is 100%, and the SOC of the batteries of EV 2 and 3 are 80%. As a result, the battery of EV 1 discharged until 16:00, and the batteries of EV 2 and 3 discharged until 15:00. For this method to be

Table 4 Comparison between production scheduling and proposed method

	Production scheduling	Proposed method
Technology	AI algorithm	EV battey
Reduced electricity rates per day	4,152 KRW	7,286 KRW
Reduced electricity rates per month	95,496 KRW	167,578 KRW
Initial cost	Algorithm development	bi-directional charger
Space requirement	Unnecessary	Existing parking space
Challenge	Distrust between workers and AI application	Battery life and reward for EV owners

applied successfully, the factory owner must provide an economic reward to the EV owner when the EV is discharged. In this paper, we consider the reward between EV charging costs during off-peak periods and electricity rates during the peak periods of the factory.

5. Conclusion

This paper presents the method of energy management using EV batteries for factories. A day-ahead power consumption prediction model for the factory based on LSTM designed to analyze production scheduling among the methods for factory energy management. The impremented production scheduling was analyzed through the designed power consumption prediction model. The method of factory energy management using the EV batteries was considered the TOU and SOC. EV batteries charged at relatively cheap electricity rates are discharged during the factory's peak load period and the period when the most expensive electricity rates are charged. Discharges at peak periods are limited considering the mobility of EV owners. This method was analyzed through PSCAD/EMTDC simulations for factory energy management when EV batteries are discharged during peak periods. Electricity rates of saved electricity rates are calculated based on the TOU. This paper is a conceptual paper that involves EVs in factory energy management and is expected to be applied as a method for factory energy management.

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박 남 기 (Nam-Gi Park)
- 학생회원
- 국립창원대학교 전기공학과 학사
- 국립창원대학교 전기공학과 석사
- (현재) 국립창원대학교 전기공학과 박사과정
- 관심분야 : 산업제조 지능화, 전력시스템

이 석 주 (Seok-Ju Lee)
- 정회원
- 국립창원대학교 전기공학과 학사
- 국립창원대학교 전기공학과 석사
- 국립창원대학교 전기공학과 박사
- (현재) 국립창원대학교 메카트로닉스 연구원 연구교수
- 관심분야 : 산업제조 지능화, 풍력 발전시스템 상태진단, 예지보전, 초전도 시스템, 디지털 트윈 시스템

고 병 수 (Byeong-Soo Go)
- 정회원
- 국립창원대학교 전기공학과 학사
- 국립창원대학교 전기공학과 석사
- 국립창원대학교 전기공학과 박사
- (현재) 국립창원대학교 메카트로닉스 연구원 연구교수
- 관심분야 : 산업제조 지능화, 풍력 발전시스템, 초전도 시스템, 디지털 트윈 시스템

딘 민차 우 (Minh-Chau Dinh)
- 준회원
- 하노이과학기술대학교 전기공학과 학사
- 국립창원대학교 전기공학과 석사
- 국립창원대학교 전기공학과 박사
- (현재) 국립창원대학교 메카트로닉스 연구원 연구교수
- 관심분야 : 산업제조 지능화, 전력시스템, 풍력발전시스템 상태진단, 예지보전, RTDS/RSCAD

이 준 엽 (Jun-Yeop Lee)
- 학생회원
- 국립창원대학교 전기공학과 학사
- 국립창원대학교 전기공학과 석사
- (현재) 국립창원대학교 전기공학과 박사과정
- 관심분야 : 산업제조 지능화, 풍력 발전시스템 상태진단, 예지보전, 초전도 시스템, 디지털 트윈 시스템

박 민 원 (Minwon Park)
- 정회원
- 국립창원대학교 전기공학과 학사
- 일본오사카대학교 전기공학과 석사
- 일본오사카대학교 전기공학과 박사
- (현재) 국립창원대학교 전기공학과 교수
- 관심분야 : 산업제조 지능화, 신재생 에너지, 전력시스템, RTDS/RSCAD