

## **Energy Management System**

### **Technical Field**

The present invention relates, in general terms, to an energy management system, and also relates to methods of optimizing performance of an energy dispatch system.

### **Background**

The emergence of new energy sources has promoted the rapid development of distributed power sources. The microgrid system realizes the integrated operation of distributed generation and load, and provides an effective technical means for the comprehensive utilization of renewable energy. The energy management system (EMS) is used by operators of electric utility grids to monitor, control, and optimize the performance of the microgrid system.

Most of the existing EMSs are either offered by battery system manufacturers or third-party manufacturers. Those EMSs offer rule-based management logic only, and can only ensure that there is no blackout at the site and there is always enough power available for dispatch. In other words, such EMSs are not intelligent since they are not able to dispatch the energy generation assets in a manner that results in reduced long-term costs of the microgrid, while taking into account the overall health of the assets.

It would be desirable to overcome all or at least one of the above-described problems.

### **Summary**

Disclosed herein is a computer-implemented method for optimizing performance of an energy dispatch system, comprising:

- creating a digital twin representing the energy dispatch system, the digital twin having a current operational behavior of the energy dispatch system;
- receiving future forecast data for a future time period;

identifying a set of initial setpoints for controlling the current operational behavior;

predicting, by the digital twin, one or more objective values based on the set of initial setpoints, the current operational behavior and the future forecast data; and

applying an optimization model to the set of initial setpoints, based on the one or more objective values, to produce an optimized set of setpoints for controlling the energy dispatch system.

In some embodiments, identifying the set of initial setpoints comprises identifying the set of initial setpoints from a plurality of setpoints, based on the future forecast data.

In some embodiments, the method further comprises receiving a plurality of past forecast data corresponding to the future forecast data and a set of setpoints for each past forecast data.

In some embodiments, identifying the set of initial setpoints comprises selecting the set of setpoints corresponding to a best past performance of the energy dispatch system.

In some embodiments, the past forecast data and the future forecast data comprise one or more of meteorological data and load demand data.

In some embodiments, the future forecast data and the past forecast data are forecast based on one or more of weather forecast, trends in historical data, and configuration of the energy dispatch system.

In some embodiments, the optimization model comprises one or more of particle swarm and stochastic programming.

In some embodiments, the method further comprise operating the energy dispatch system according to the optimized set of setpoints.

In some embodiments, the method comprises collecting operation data describing an operational behavior of the energy dispatch system for the future time period.

In some embodiments, the method comprises updating the current operational behavior based on the operational behavior of the energy dispatch system for the future time period.

In some embodiments, the method comprises updating the digital twin based on the current operational behavior.

A system for optimizing performance of an energy dispatch system, comprising:

- a memory;

- a training module configured to provide a digital twin representing the energy dispatch system, the digital twin having a current operational behavior of the energy dispatch system;

- a receiving module for receiving future forecast data for a future time period;

- a processor configured to identify a set of initial setpoints for controlling the current operational behavior;

- a predicting module comprising the digital twin configured to predict one or more objective values based on the set of initial setpoints, the current operational behavior and the future forecast data; and

- an optimization model configured to be applied to the set of initial setpoints to produce an optimized set of setpoints for controlling the energy dispatch system, based on the one or more objective values.

In some embodiments, the processor is configured to identify the set of initial setpoints by identifying the set of initial setpoints from a plurality of setpoints, based on the future forecast data.

In some embodiments, the processor is configured to receive a plurality of past forecast data corresponding to the future forecast data and a set of setpoints for each past forecast data, wherein the processor is configured to identify the

set of initial setpoints by selecting the set of setpoints corresponding to a best past performance of the energy dispatch system.

In some embodiments, the system further comprises an operating module for operating the energy dispatch system according to the optimized set of setpoints.

In some embodiments, the operating module is configured to collect operation data describing an operational behavior of the energy dispatch system for the future time period.

In some embodiments, the operating module is configured to update the current operational behavior based on the operational behavior of the energy dispatch system for the future time period.

In some embodiments, the training module is configured to update the digital twin based on the current operational behavior.

### **Brief description of the drawings**

Embodiments of the present invention will now be described, by way of non-limiting example, with reference to the drawings in which:

Figure 1 is a flow diagram showing a method used for optimizing performance of an energy dispatch system;

Figure 2 shows an example digital twin for predicting the performance of an energy dispatch system;

Figure 3 is a schematic diagram showing components of a system used for optimizing performance of an energy dispatch system; and

Figure 4 is a schematic diagram showing components of an exemplary computer system for performing the methods described herein.

**Detailed description**

The present disclosure relates to an integrated system and method for managing energy generation and consumption of energy dispatch systems. In some embodiments, the energy dispatch systems are microgrids, which are self-sufficient energy platforms that serve discrete geographic footprints, such as a college campus, hospital complex, and business centre. Within microgrids are one or more kinds of distributed energy, such as solar panels, wind turbines, combined heat and power and power storage devices (batteries). The integrated system consists of modules for real-time data analysis and remote automatic power management. Said integrated systems allow reducing the cost of energy and ensuring optimal operation of the equipment in the energy dispatch systems, while without the need for manual control to optimize energy generation.

Data on energy consumption, environment parameters and energy dispatch system's activity is collected and stored on a day-to-day basis. In some embodiments, the proposed system forecasts the real-time consumption and generation patterns of the energy dispatch system for the coming one to two days or some other predetermined period. The collected data is analyzed for a variety of purposes. First, the proposed system allows pre-determining setpoints of the monitored energy dispatch system by analyzing the captured data. Said setpoint refers to a desired or target value of the energy dispatch system. It will be appreciated that the pre-determined setpoints may not be the optimal value. In addition, the collected data is also used for predicting the dynamics of energy generation and consumption in the monitored energy dispatch system during a specific time, for example a day or a week. This invention operates on the basis of digital twin to achieve said predicting function. It will be appreciated that this invention allows using relationships based on empirical models, and also allows using a balance of systems approach as well as system interactions. Said predictive model also allows the possibility to reduce the initial costs of creating a power supply system, especially at the stage of design and construction of the energy dispatch system.

The present disclosure also related to an energy management and control solution. The user of the proposed system is able to control the power generation subject to the limitations set by the user. The proposed system comprises a controller that optimizes the performance of the energy dispatch system due to artificial intelligence, e.g. machine learning algorithms such as particle swarm and stochastic programming. Based on the data accumulated at the monitored energy dispatch systems, the proposed system is able to search for an optimized setpoint that gives the most promising energy generation and consumption optimization options or performance. The energy dispatch system is then operated according to the optimized setpoints. The actual operation behavior data of the energy dispatch system is then recorded and sent back to the digital twin. Said digital twin will update the estimate of the performance of the energy dispatch system based on said actual operation behavior data to make the digital twin more accurate.

By updating the digital twin based on the actual operation behavior data from the energy dispatch system, the digital twin changes to account for degradation in performance of the power generation assets or dispatch systems over time. This also helps account for upgrades, such as replacement solar panels and the like, that change the operational behavior.

Figure 1 illustrates an example computer-implemented method 100 for optimizing performance of an energy dispatch system. Broadly, the method 100 comprises:

- Step 102: creating a digital twin representing the energy dispatch system, the digital twin having a current operational behavior of the energy dispatch system;

- Step 104: receiving future forecast data for a future time period;

- Step 106: identifying a set of initial setpoints for controlling the current operational behavior;

- Step 108: predicting, by the digital twin, one or more objective values based on the set of initial setpoints, the current operational behavior and the future forecast data; and

Step 110: applying an optimization model to the set of initial setpoints, based on the one or more objective values, to produce an optimized set of setpoints for controlling the energy dispatch system.

The purpose of Step 102 is to create a digital twin representing the actual energy dispatch system. In the present disclosure, the digital twin refers to a virtual representation that serves as the digital counterpart of the energy dispatch system. The digital twin concept consists of three distinct parts: the energy dispatch system in the physical environment, the digital counterpart, and the connections between the energy dispatch system and the digital counterpart. In some embodiments, said connections is data that flows from the energy dispatch system to the digital counterpart and information that is available from the digital counterpart to the physical energy dispatch system. The digital twin takes inputs, and outputs the simulation data for minute-by-minute daily power output of each component (e.g. genset power, battery power, state of charge (SOC), and photovoltaic (PV) production) of the energy dispatch system in advance. In such case, the digital twin is meant to be an up-to-date and accurate copy of the energy dispatch system's properties and states as it can be used to view the status of the actual energy dispatch system, which provides a way to project the physical energy dispatch system into the digital world. As will be discussed in detail, said digital twin can be periodically updated to improve its simulation accuracy. In one embodiment, when sensors collect data from a device connected to the energy dispatch system, the sensor data can be compared with the performance parameters predicted by the digital twin to improve the digital twin's accuracy in real time.

The digital twin has a current operational behavior of the energy dispatch system. Said current operational behavior refers to the performance simulated by the digital twin which is representing the energy dispatch system operating at the current time period. The operational behavior of the energy dispatch system may be time-series data and change from time to time. The current operational behavior may be one or more of the simulation performance of genset, PV and battery of the energy dispatch system.

In one embodiment, the digital twin that represents the energy dispatch system that operates at the current time period (i.e.,  $t_1$ ) is first created. Then, the future forecast data for period  $t_2$  is received (i.e., Step 104). It will be appreciated that  $t_2 > t_1$ . In such case, the future forecast data is generated for power generation and load to simulate the future behavior of the energy dispatch system, and/or future conditions in which the system will operate (e.g. variations in power demand based on variation in the number of people using power, variations in weather conditions and so on), at time  $t_2$  by the digital twin. The future forecast data is time-series data and may change over time. In the present disclosure, forecasts are essential for the estimation of the generation of renewable power and consumption.

In the present disclosure, the energy dispatch system is a microgrid. A microgrid is a decentralized group of electricity sources and loads that normally operates connected to and synchronous with the traditional wide areas synchronous grid, but is also able to disconnect from the interconnected grid and function autonomously in "island mode". In some embodiments, there may be a plurality of distinct microgrids that exist. While the underlying principles for microgrids are similar, different microgrids have different configurations and components. Hence, the digital twin for each microgrid will be distinct. A good digital twin should be able to predict the power output of a microgrid assets accurately. Also, if two or more microgrids have similar brand of battery/PV/diesel genset components, the data from one microgrid can be used to learn the behavior and integrate the learnt behavior in the simulation or digital twin for the other, similar microgrid(s).

The present invention considers two types of forecast. The first forecast is weather forecast focusing on irradiance and temperature. Said weather forecast can be obtained from the satellite data. In one embodiment, the purpose of the weather forecast is determination of PV production output for simulation of site energy generation for the future time period. The second forecast is called load forecast that can be obtained from in-house historical data and algorithms. In one embodiment, the purpose of said load forecast is to determine load demand for simulation of site energy consumption for the future time period. For example, weekend power demand at hotels is often far greater than demand

during the week, and peak holiday periods will demand more power throughout the week for the off-peak periods.

Step 106 aims to identify a set of initial setpoints for controlling the current operational behavior. As used herein, a "set", such as a "set of setpoints" may comprise one or more items, such as one or more setpoints. In the present disclosure, "controlling the current operational behavior" means the same thing in this context as "controlling the energy dispatch system". Said setpoint refers to the desired or target value for an essential variable, or process value of the energy dispatch system. In one embodiment, the proposed method 100 makes decisions on the amount of power to be dispatched from the energy dispatch system at any time. This is done by using a so called energy management system (EMS) logic. Said EMS logic takes the setpoints as inputs.

Regarding setpoints: assuming an energy dispatch system, where battery, PV and load are operational as power generation sources at time  $t - 1$ . The genset can be turned on for generation if SOC of battery drops below 20%, which is the setpoint for the EMS logic. To be specific, the EMS logic for genset in this example is: turning on the genset when battery SOC is lower than the setpoint 20%. In some embodiments, said 20% setpoint is fixed mainly at the time of the commissioning of the site and stays unchanged since then. Another setpoint may be that power can only be switched from mains or fossil fueled generator power to/from green or renewable power a fixed number of times per predetermined period – e.g. one or two days.

One problem is that the setpoints, which are often defined by the manufacturers of the energy dispatch system, always stay constant even when the energy dispatch system degrades or weather changes over time. Thus, the concept that internal factors and external factors are constant is only possibly accurate when those factors are set. Internal factors are subject to change, such as the condition or wear of the system, whether or not power generation capacity remains constant, malfunctioning components, the ability of components to sustain being switched ON/OFF, replacements or repairs and so on. Similarly, external factors are subject to change, such as weather conditions, year-on-year demand variation, and so on. The static setpoints and their inability to

change often leads to degraded performance of prior energy dispatch systems. The aim of the present disclosure is to implement setpoints that are in line with performance goals of the energy dispatch system.

The quantitative measures of the performance of the energy dispatch system could be included in the objective function of the optimization. In an example, fuel consumption is taken as a measure of the success of the energy dispatch system. In such case, the aim of method 100 is to identify setpoints that lead to reduction in the fuel consumption. For the above-mentioned example, the fixed setpoint (e.g. 20%) may not be the optimal on a sunny day. This is because on a sunny day the PV power may be high enough to charge the battery and supply the load around for example 8AM. Therefore, the genset does not need to be turned on in the morning hours at 7AM if the SOC drops to 20%. In fact, to reduce the instances of genset switching on and consuming fuel, the setpoint may be changed to a lower value (e.g. 15%) for this day to reduce the instances of genset switching on and reduce fuel consumption. In another example, the number of times the genset is turned on/off is taken as a measure of the success of the energy dispatch system. Originally, the genset is turned on when the SOC falls below a lower limit (e.g. 20%) and turned off when the SOC is above an upper limit (e.g. 40%). In this example, said 20% and 40% are setpoints. To reduce the number of times the genset is turned off, the upper limit can be changed from 40% to 60%. Similarly, to reduce the number of times the genset is turned on, the lower limit in one example can be changed from 20% to 10%.

In the present invention, two types of setpoints are considered for further simulation and optimization. The first type is time-based setpoints. Said time-based setpoints may include start and stop time of the genset or a minimum running period once switched on. It may also include time for entering the day-mode or night mode for EMS. It will be appreciated that a traditional EMS has a night mode and a day mode for the logic. The second type is asset-related setpoints, which includes SOC threshold to start the genset, SOC threshold to stop the battery from discharging, target genset power at any instant of time, and battery charging power limit.

At Step 106, to identify the set of initial setpoints, a plurality of setpoints are randomly selected at first to complete at least one simulation at Step 108 and 110. In one embodiment, a random set of setpoints [20%, 30%, 40%, 70%, 80%] is generated. Identifying the set of initial setpoints may further comprise receiving a plurality of past forecast data corresponding to the future forecast data and a set of setpoints for each past forecast data. In some embodiments, the past forecast data and the future forecast data comprise one or more of meteorological data and load demand data. The future forecast data and the past forecast data may be forecast based on one or more of weather forecast, trends in historical data, and configuration of the energy dispatch system.

In the above example, the present disclosure will then receive a weather forecast data (e.g. Monday is a sunny day) created on the past date (e.g. Monday). Said weather forecast data created on Monday corresponds to the weather forecast data made on the future date (e.g. Tuesday). Identifying the set of initial setpoints may comprise identifying the set of initial setpoints from said randomly selected setpoints, based on the future forecast data (i.e., the weather forecast data made on Tuesday). Identifying the set of initial setpoints may also comprise selecting the set of setpoints corresponding to a best past performance of the energy dispatch system. In the above example, it is already known from past simulation and optimization that in a sunny day such as Monday, a setpoint less than 50% would be optimal if the objective function is to reduce the instances of genset switching on and reduce fuel consumption. In such case, if the weather forecast made on Tuesday (i.e., the future forecast data) is that Tuesday is also a sunny day, the setpoints [70%, 80%] can be simply removed from the plurality of setpoints. Hence, the set of initial setpoints [20%, 30%, 40%] is generated for simulation and optimization. In general, filtering the set of initial setpoints from the plurality of setpoints is possible-one can simply remove some setpoints that appear to lead to poor performance of the energy dispatch system. It will be appreciated that filtering setpoints also brings some benefits like reducing the number of optimization iterations.

In the present disclosure, the variability of the forecasts has to be accounted for while finalizing the set of initial setpoints for the simulation. A typical process includes two steps. The first step is to find the set of initial setpoints using a

training set. For irradiance, the present disclosure generates a plurality of scenarios of time series irradiance data based on a point of the weather forecast, upper confidence interval and the lower confidence interval. Then, the set of initial setpoints that minimize the average cost over all the scenarios are chosen. The second step is to validate the setpoint performance on a validation set. In one embodiment, the validation set consists of 20 times more scenarios than training set. The present disclosure runs the optimization on the training set first and evaluate the resulting set of initial setpoints on the validation set. If the resulting set of initial setpoints perform significantly worse on the validation set, there is a need to increase the size of the training set. The aim of the variability of the forecasts is not to find better estimates of the forecast but the set of initial setpoints that account for the variability in the forecasts and could give the reduced average costs over various simulated scenarios.

Step 108 is based on the digital twin created at Step 102. Step 108 aims to predict the objective values of an objective function. The present disclosure gives five examples of the simulation logic used in the digital twin for calculating the asset power of the energy dispatch system at time  $t$  from the start of simulation to the end of simulation with  $\Delta t$  increments. It will be appreciated that the content of the following examples is site-specific and only serves as examples of the pseudocode used in the digital twin. The simulation logic may be subject to change from site to site.

The digital twin of the energy dispatch system is composed of the many parts, some of which are expressed in detail below.

### **Digital Twin Part 1**

The following function shows an example digital twin used to calculate genset power at time  $t$ :

$$\text{genset\_power}_t \leftarrow \text{genset\_power\_logic}(\text{SOC}_{t-1}, \text{genset\_power}_{t-1}, \text{setpoints}).$$

The above function is detailed by the high level pseudocode illustrated below.

```

Get the SOC thresholds (SOC_high and SOC_low) from the setpoints
if SOCt-1 > SOC_high

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    genset_powert ← 0
  else if SOCt-1 < SOC_low
    genset_powert ← the genset power setpoint
  else
    genset_powert ← genset_powert-1

```

To be specific, as shown in the above pseudocode, the genset power at time  $t$ , is a function of the SOC at previous time  $t - 1$  (i.e.,  $SOC_{t-1}$ ) and is dependent on setpoints such as SOC upper limit (i.e.  $SOC_{high}$ ), SOC lower limit (i.e.,  $SOC_{low}$ ) and maximum genset power setpoint. First, if  $SOC_{t-1}$  is higher than  $SOC_{high}$ , then the genset power is set to zero as the battery of the energy dispatch system has enough charge to supply for load. Second, if  $SOC_{t-1}$  is lower than  $SOC_{low}$ , then the genset power is set to the setpoint that is of the highest genset charging power. Third, if  $SOC_{t-1}$  is between  $SOC_{high}$  and  $SOC_{low}$ , the genset power at time  $t$  is kept the same as genset power at time  $t - 1$ .

## **Digital Twin Part 2**

Figure 2 refers to an example digital twin used to simulate battery charging power limit at time  $t$ . In particular, the SOC at previous time  $t - 1$  (i.e.,  $SOC_{t-1}$ ) is between 85 and 100. The curve refers to a logistic function,  $logistic\_function$ , fitted to the actual SOC and charging power data. The X-axis is  $SOC_{t-1}$  and Y-axis is the battery charging power limit at time  $t$  (i.e.,  $battery\_charging\_power\_limit_t$ ). Said digital twin is detailed by the pseudocode below:

```

  if SOCt-1 ≥ 100
    battery_charging_power_limitt ← 0
  else if SOCt-1 < 85
    battery_charging_power_limitt ← battery_charging_limit_bms_logic
  else
    battery_charging_power_limitt ← logistic_function(SOCt-1)

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In particular, if  $SOC_{t-1}$  is higher than or equal to 100, the battery charging power limit is set to zero. If  $SOC_{t-1}$  is lower than 85, the battery charging power limit is set to  $battery\_charging\_limit\_bms\_logic$ , which is a constant referring to the

battery charging limit set by the battery management system (BMS). In the present disclosure, the term “constants” refer to nominal power/energy values of the energy dispatch system assets. Said values can be obtained from the datasheets of the energy dispatch system assets and comprise: PV peak power, battery nominal capacity, and genset rated capacity, etc.

### **Digital Twin Part 3**

The following function shows an example digital twin used to calculate PV power at time  $t$ :

$$pv\_power_t \leftarrow calculate\_pv\_power(irradiance_t, ambient\_temperature_t,$$

$$pv\_power\_limit_t, pv\_peak\_power, pv\_derating\_factor, pv\_temperature\_coefficient,$$

where  $irradiance_t$  and  $ambient\_temperature_t$  refer to irradiance forecast and ambient temperature forecast at time  $t$ , respectively,  $pv\_power\_limit_t$  denotes PV power limit at time  $t$ ,  $pv\_peak\_power$  is a constant referring to PV peak power,  $pv\_derating\_factor$  is an asset parameter estimate referring to the PV derating factor,  $pv\_temperature\_coefficient$  is an asset parameter estimate referring to the PV temperature coefficient. In the present disclosure, said asset parameter estimates are slowly changing variables and are time-dependent due to the degradation of the energy dispatch system assets with time. The initial values at time  $t = 0$  could be obtained from datasheets of the assets. Said asset parameter estimates can be calculated using the current operational behavior data and tuned using the feedback module. The asset parameter estimates may include: estimates of the charge stored in battery (e.g. total battery capacity), asset losses (e.g. cable transmission losses and shading losses), PV derating factor which is dependent on the maximum temperature of the PV panels, degradation rates for wind equipment/biogas/combined heat and power (CHP), capacitance of a capacitor bank, and efficiency estimates (e.g. DC/AC efficiency of the ESS, generation efficiency of genset, and wind turbines).

The above overarching function consists of the following sub-functions.

$$cell\_temperature_t \leftarrow cell\_temperature\_formula(irradiance_t, ambient\_temperature_t),$$

$$pv\_power\_before\_curtailment_t \leftarrow pv\_peak\_power * \frac{irradiance_t}{1000} * (1 + (cell\_temperature_t - 25) * pv\_temperature\_coefficient) * pv\_derating\_factor.$$

As will be discussed later, the forecasts for irradiance and ambient temperature are available. Based on this, the cell temperature at time  $t$  (i.e.,  $\text{cell\_temperature}_t$ ) can be calculated by the digital twin. The PV power before curtailment at time  $t$  (i.e.,  $\text{pv\_power\_before\_curtailment}_t$ ) is a function of irradiance and panel cell temperature. The temperature coefficient and PV derating factor are used to calculate the PV power after considering temperature losses and other PV losses.

It will be appreciated that the battery charging power limit at time  $t$  (i.e.,  $\text{battery\_charging\_power\_limit}_t$ ) can be calculated based on the following function:

$$\text{battery\_charging\_power\_limit}_t \leftarrow \text{battery\_charging\_power\_limit\_logic}(\text{SOC}_{t-1}).$$

The PV power limit at time  $t$  (i.e.,  $\text{pv\_power\_limit}_t$ ) can be calculated using the following function.

$$\text{pv\_power\_limit}_t \leftarrow \text{load\_power}_t + \text{battery\_charging\_power\_limit}_t.$$

It is important to note that PV needs to provide for load and battery at any given point of time, hence  $\text{pv\_power\_limit}_t$  needs to be equal to the sum of the load power at time  $t$  (i.e.,  $\text{load\_power}_t$ ) and the battery charging power limit at time  $t$  (i.e.,  $\text{battery\_charging\_power\_limit}_t$ ).

We would like to emphasize that the PV power can be curtailed based on the PV power limit available for production at time  $t$  (i.e.,  $\text{pv\_power\_limit}_t$ ). In particular,  $\text{pv\_power\_limit}_t$  is calculated according to:

$$\text{pv\_power}_t \leftarrow \min(\text{pv\_power\_before\_curtailment}_t, \text{pv\_power\_limit}_t).$$

In some embodiments, if PV power produced before curtailment,  $\text{pv\_power\_before\_curtailment}_t$  is larger than the available PV power limit (i.e.,  $\text{pv\_power\_limit}_t$ ) the excess PV power will be curtailed and the PV to be produced at time  $t$  is set to produce as per the defined limit (i.e.,  $\text{pv\_power\_limit}_t$ ). In such case,  $\text{pv\_power}_t$  can be simulated using the above equation.

#### **Digital Twin Part 4**

The following function shows an example digital twin used to calculate battery power at time  $t$ .

$$\text{battery\_power}_t \leftarrow \text{load\_power}_t - \text{pv\_power}_t - \text{genset\_power}_t.$$

For the energy dispatch system, the demand must meet the supply. As shown in the function above, the battery power at time  $t$  in the present disclosure is calculated by finding the difference between the power demand at time  $t$  (i.e.,  $\text{load\_power}_t$ ) and total power available at time  $t$  (i.e., the sum of PV power at time  $t$  (i.e.,  $\text{pv\_power}_t$ ) and genset power at time  $t$  (i.e.,  $\text{genset\_power}_t$ )).

### **Digital Twin Part 5**

The following pseudocode shows an example digital twin used to calculate SOC at time  $t$  (i.e.,  $\text{SOC}_t$ ). In the present disclosure,  $\text{SOC}_t$  is calculated using the battery power, nominal capacity of the battery and the AC/DC efficiency of the battery.

$$\text{SOC}_t \leftarrow \text{calculate\_SOC}(\text{battery\_power}_t, \text{SOC}_{t-1}, \Delta t, \text{battery\_capacity}, \text{battery\_ac\_dc\_efficiency}, \text{battery\_dc\_dc\_efficiency}, \text{battery\_dc\_ac\_efficiency}).$$

In particular,  $\text{battery\_capacity}$  is a constant referring to the nominal capacity of the battery,  $\text{battery\_ac\_dc\_efficiency}$  is a constant referring to the battery AC/DC efficiency,  $\text{battery\_dc\_dc\_efficiency}$  is a constant referring to the battery DC/DC efficiency,  $\text{battery\_dc\_ac\_efficiency}$  is a constant referring to the battery DC/AC efficiency. Said digital twin is detailed by the pseudocode below:

```

if battery_power_t > 0:
    SoC_t ← SoC_{t-1} - ((battery_power_t * Δt) / battery_dc_ac_efficiency) / battery_capacity * 100
else:
    SoC_t
    ← SoC_{t-1} - battery_power_t
    * Δt * battery_ac_dc_efficiency * battery_dc_dc_efficiency / battery_capacity * 100

```

The digital twin is then used for optimizing the performance and utilization of the energy dispatch system. As will be discussed in details, the optimization works to find the set of setpoints that give the most optimized objective function or reduced costs out of the simulations.

At Step 110, an optimization model is applied to the set of initial setpoints, based on the objective values, to produce an optimized set of setpoints for controlling the energy dispatch system. In general, the aim of the optimization

is to have optimal performance of assets and lower the costs incurred from the energy dispatch system operation. In the present disclosure, the term “cost” and “objective function” are used interchangeably. The costs can be summarized in different types. The first kind of costs is called operational fuel costs. In particular, the purpose of the energy dispatch system is to reduce the costs incurred from the diesel fuel used. The second kind of costs are operations and maintenance (O&M) costs. In particular, PV, battery, diesel generator and electrical devices such as circuit breakers, relay switches are all mechanical and electrical assets that are prone to degradation. It will be appreciated that efficient and a less strenuous usage on a daily basis lead to less chances of breakdown in the long-term and reduced O&M costs. The third kind of costs are system instability costs. The reason for introducing such costs is that the fluctuations in the frequency and power of the devices can damage the devices on site due to sudden fluctuations in current or reverse current. Last but not least, there are also other kinds of costs such as the environment cost measured through energy penetration and total carbon emissions.

We would like to emphasize that the choice of objective function may have impact on associated costs. For example, if the goal is to lower fuel usage, its impact on associated costs would be to reduce fuel costs. If the objective function is to find maximum renewable energy penetration, the impact on associated costs would be to reduce diesel costs or environmental costs. When the goal is to seek fewer genset start/stop switches, the impact on associated costs would be to find less fuel consumed (as cranking up of genset requires more fuel than when genset is in operation), or to enable grid forming element to change less frequently, or to seek less system instability costs, or to achieve less mechanical wear and tear of the switch. If the objective function is to find the least fluctuation in power, the impact on associated costs would be to look for the lowest system instability costs. If the goal is to reduce battery cycles, the impact on associated costs would be to reduce O&M costs for the battery. In fact, battery operation hours and the warranty conditions are adhered to as batteries may be required to be operated at one cycle per day for max. If the objective function is to find the least instances of under-loading of genset (e.g. power is less than 30% of genset rated capacity) and over-loading (e.g. power is more than 80% of the genset rated capacity), the impact on associated costs

would be to seek lower O&M costs of the genset due to the fact that under-loading and over-loading of the genset may be damaging for the genset.

An example of the objective function is illustrated below. In particular, there are three objectives 01, 02, and 03. The objective 01 is related to fuel cost. Typically, 01 contains the total fuel consumption and fuel saved from operation of controllable renewable energy asset. The objective 02 is related to asset performance, i.e., the number of switches of the genset on/off. The objective 03 is related to O&M costs, i.e., the number of battery cycles per day. The above three objectives may be combined by assigning weights to each of the objectives. The purpose of adding weights is to scale objectives for each comparison and indicate relative importance for each of the objectives. In some embodiments, the weights are assigned subjectively by the engineers on site. It will be appreciated that different energy dispatch systems may specify different importance for each of the objective function.

Constraints, which refer to restrictions that need to be fulfilled by the optimization, may be introduced at Step 110. In the present disclosure, a plurality of constraints are considered while during the optimization stage of the method 100. The first constraint is that there should be no blackout at the energy dispatch system. Second, the battery is required to be operated at certain times per day for max 1 cycle per day. Third, the genset is only allowed to start/stop no more than a certain number of times per day. Last but not least, the genset is not recommended to run at a power below a certain % of its rated capacity as it leads to underloading and possible wet stacking. It will be appreciated that the constraint and objective may be conflicting. In one embodiment, the objective is to minimize the number of start/stop of the genset, whereas the constraint would be to have no blackout at the site. In such case, when PV is not available and the battery is out of charge, the genset will need to be turned on. Obviously, the objective cannot be set to zero.

In some embodiments, the optimization model used at Step 110 comprises one or more of particle swarm and any other stochastic programming optimization technique. Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with

regard to a given measure of quality. It solves the optimization problem by having a population of candidate solutions, and moving these solutions around in the search space. This is expected to move the solution toward the best solutions. A detailed logic of the PSO optimization algorithm is illustrated below. In the first step, a function  $f$  that maps a vector  $x$  to  $f(x)$  is determined, where  $x$  refers to the set of initial setpoints. In the present disclosure,  $f(x)$  denotes the objective function. In the second step, initial vectors  $[x_1, x_2, \dots, x_n]$  are determined, where  $n$  denotes the number of candidate solutions as input into the PSO. In the third step, objective functions  $[f(x_1), f(x_2), \dots, f(x_n)]$  are being evaluated, and accordingly  $[x_1, x_2, \dots, x_n]$  are updated based on the evaluation results. The third step typically needs to be repeated multiple times so as to find an optimal  $x^*$  such that the objective function  $f(x^*)$  is optimal.

In some embodiments, the method 100 further comprises operating the energy dispatch system according to the optimized set of setpoints (Step 112, Figure 1). In particular, the optimization algorithm recommends the optimized set of setpoints with the optimal objective function. Said optimized set of setpoints are then sent to the cloud and implemented at the energy dispatch system. Then, the method 100 further comprises collecting operation data describing an operational behavior of the energy dispatch system for the future time period (Step 114, Figure 1). In one embodiment, the operation data describing the operational behavior of the energy dispatch system for the future time period is collected by the onsite data acquisition device or data logger and sent back to the digital twin. Table 1 illustrates examples of the operation data collected. The operation data can be collected by a Modbus protocol or analog. The entire Energy Storage System (ESS) In Table 1 consists of several clusters. The battery inverter is connected to each battery cluster, through which the cluster data can be collected. In the present disclosure, each genset has a genset controller unit which is able to collect data representing the diesel generator. The entire energy dispatch system is split into multiple load groups, and a power meter can be used to collect the data for each of the load groups.

**Table 1**

| Asset | Operation data collected |
|-------|--------------------------|
|-------|--------------------------|

|                       |                                                                                                                                                                                                                                                                                                                                                                                          |
|-----------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| PV                    | <ul style="list-style-type: none"> <li>• 3- phase current and voltage for each PV string inverter</li> <li>• active power for each PV string inverter</li> <li>• frequency for each PV string inverter</li> <li>• DC current/voltage for each maximum power point tracking (MPPT) when each PV inverter is connected to 1 or 2 MPPTs depending on the inverter configuration.</li> </ul> |
| ESS                   | <ul style="list-style-type: none"> <li>• battery DC current/voltage/temperature</li> <li>• active/reactive/apparent power</li> <li>• frequency</li> <li>• SOC</li> </ul>                                                                                                                                                                                                                 |
| Diesel Generator      | <ul style="list-style-type: none"> <li>• genset frequency</li> <li>• 3 Phase current</li> <li>• 3 Phase Voltage</li> <li>• RPM speed of each genset</li> <li>• genset starter battery voltage</li> <li>• oil pressure</li> <li>• active power</li> </ul>                                                                                                                                 |
| Load Consumption Side | <ul style="list-style-type: none"> <li>• active/reactive/apparent power</li> </ul>                                                                                                                                                                                                                                                                                                       |
| Sensor Data           | <ul style="list-style-type: none"> <li>• irradiance sensor data (collected by tilt irradiance sensor/pyrometer)</li> <li>• PV panel cell temperature data (collected by module temperature sensor)</li> <li>• ambient temperature data (collected by temperature sensor)</li> </ul>                                                                                                      |

In the present disclosure, the collected data as illustrated in Table 1 is configured to go to a data acquisition device such as PC or I/O modules, where I/O refers to input/output. Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems typically convert analog waveforms into digital values for processing. The collected data will then go to a data acquisition device, consisting of PC, surge arrestors, relay switches and a Human Machine Interface (HMI). Said HMI refers to a dashboard or screen used to control machinery. It can be relied on to translate complex data into useful information. The minute-by-minute data for every asset is collected in the PC and transferred to the cloud database using local internet connection at the energy dispatch system site.

As discussed before, the real data related to the operational behavior of the energy dispatch system can be used for feedback of the digital twin, such that future estimates of the simulation generated by the digital twin could be more

accurate. Remark that the real data related to the operational behavior of the energy dispatch system is machine collected data, therefore, there could be some outliers or instances of missing said real data. This problem can be resolved in two different ways. The first method is outlier identification and removal. In particular, the upper and lower limits of the data are specified as meta-data. If the outlier (i.e., data outside the normal range) is observed, then the data is removed and filled as missing data. The second method is to remove days with the missing data. To be specific, the optimization at Step 110 will require complete entire days' data for the simulation and optimization of setpoints. Those days with missing data will not feed back to the system.

It will be appreciated that the real data as shown in Table 1 is also those kinds of data that the digital twin aims to simulate. In some embodiments, the method 100 comprises updating the current operational behavior based on the operational behavior of the energy dispatch system for the future time period. The method 100 also comprises updating the digital twin based on the current operational behavior (Step 116, Figure 1). The digital twin will update its estimate of the energy dispatch system based on the current operational behavior to make the simulation result more accurate. In particular, the electrical data of the site is obtained using the data logger or data acquisition device and stored in the cloud. This current operational behavior is compared against the estimates of the same electrical data from the simulation provided by the digital twin. After the setpoints implementation, the actual system behavior data and simulated data using same setpoints is compared. The aim is to minimize the absolute error between the actual system behavior data and simulated data. Said absolute error can be represented as:

$$\text{Absolute Error}_t = \text{Simulation Estimate(PV active power)}_t - \text{Real data (PV active power)}_t.$$

The above function is time-series. Said absolute error can be minimized by tuning the asset parameter estimates in the simulation. A stochastic optimization technique, like PSO, may also be used to select the best set of electrical system info that minimizes the error between the simulated daily profile of the energy dispatch system assets and actual daily profile of the energy dispatch system assets.

Figure 3 illustrates an example system 200 for optimizing performance of an energy dispatch system. Broadly, the system 200 comprises:

- a memory 202;
- a training module 204 configured to provide (e.g. create or source from memory) a digital twin representing the energy dispatch system, the digital twin having a current operational behavior of the energy dispatch system;
- a receiving module 206 for receiving future forecast data for a future time period;
- a processor 208 configured to identify a set of initial setpoints for controlling the current operational behavior;
- a predicting module 210 comprising the digital twin configured to predict one or more objective values based on the set of initial setpoints, the current operational behavior and the future forecast data; and
- an optimization model 212 configured to be applied to the set of initial setpoints to produce an optimized set of setpoints for controlling the energy dispatch system, based on the one or more objective values.

In some embodiments, the processor 208 is configured to identify the set of initial setpoints by identifying the set of initial setpoints from a plurality of setpoints, based on the future forecast data. The processor 208 may be configured to receive a plurality of past forecast data corresponding to the future forecast data and a set of setpoints for each past forecast data. In some examples, the processor 208 is configured to identify (e.g. generate or select) the set of initial setpoints by selecting the set of setpoints corresponding to a best past performance of the energy dispatch system. It will be appreciated that filtering the set of initial setpoints from the plurality of setpoints is possible. That is, one can simply remove some setpoints that appear to lead to poor performance of the energy dispatch system. It will be appreciated that filtering setpoints also brings some benefits like reducing the number of optimization iterations.

In some embodiments, the system 200 further comprises an operating module 214 for operating the energy dispatch system according to the optimized set of setpoints. The operating module 214 may be configured to collect operation

data describing an operational behavior of the energy dispatch system for the future time period. The operating module 214 may be configured to update the current operational behavior based on the operational behavior of the energy dispatch system for the future time period.

In some embodiments, the training module 204 is configured to update the digital twin based on the current operational behavior. The real data related to the operational behavior of the energy dispatch system can be used for feedback of the digital twin, such that future estimates of the simulation generated by the digital twin could be more accurate. After the setpoints implementation, the actual system behavior data and simulated data using same setpoints can be compared so as to minimize the absolute error between the actual system behavior data and simulated data.

Figure 4 is a block diagram showing an exemplary computer device 300, in which embodiments of the invention may be practiced. The computer device 300 may be a mobile computer device such as a smart phone, a wearable device, a palm-top computer, and multimedia Internet enabled cellular telephones, an on-board computing system or any other computing system, a mobile device such as an iPhone™ manufactured by Apple™, Inc or one manufactured by LG™, HTCTM and Samsung™, for example, or other device.

As shown, the mobile computer device 300 includes the following components in electronic communication via a bus 306:

- (a) a display 302;
- (b) non-volatile (non-transitory) memory 304;
- (c) random access memory ("RAM") 308;
- (d) N processing components 310;
- (e) a transceiver component 312 that includes N transceivers; and
- (f) user controls 314.

Although the components depicted in Figure 4 represent physical components, Figure 4 is not intended to be a hardware diagram. Thus, many of the components depicted in Figure 4 may be realized by common constructs or distributed among additional physical components. Moreover, it is certainly

contemplated that other existing and yet-to-be developed physical components and architectures may be utilized to implement the functional components described with reference to Figure 4.

The display 302 generally operates to provide a presentation of content to a user, and may be realized by any of a variety of displays (e.g., CRT, LCD, HDMI, micro-projector and OLED displays).

In general, the non-volatile data storage 304 (also referred to as non-volatile memory) functions to store (e.g., persistently store) data and executable code. The system architecture may be implemented in memory 304, or by instructions stored in memory 304.

In some embodiments for example, the non-volatile memory 304 includes bootloader code, modem software, operating system code, file system code, and code to facilitate the implementation components, well known to those of ordinary skill in the art, which are not depicted nor described for simplicity.

In many implementations, the non-volatile memory 304 is realized by flash memory (e.g., NAND or ONENAND memory), but it is certainly contemplated that other memory types may be utilized as well. Although it may be possible to execute the code from the non-volatile memory 304, the executable code in the non-volatile memory 304 is typically loaded into RAM 308 and executed by one or more of the N processing components 310.

The N processing components 310 in connection with RAM 308 generally operate to execute the instructions stored in non-volatile memory 304. As one of ordinary skill in the art will appreciate, the N processing components 310 may include a video processor, modem processor, DSP, graphics processing unit (GPU), and other processing components.

The transceiver component 312 includes N transceiver chains, which may be used for communicating with external devices via wireless networks. Each of the N transceiver chains may represent a transceiver associated with a particular communication scheme. For example, each transceiver may

correspond to protocols that are specific to local area networks, cellular networks (e.g., a CDMA network, a GPRS network, a UMTS networks), and other types of communication networks.

The system 300 of Figure 4 may be connected to any appliance 418, such as one or more cameras mounted to the vehicle, a speedometer, a weather service for updating local context, or an external database from which context can be acquired.

It should be recognized that Figure 4 is merely exemplary and in one or more exemplary embodiments, the functions described herein may be implemented in hardware, software, firmware, or any combination thereof. If implemented in software, the functions may be stored on or transmitted over as one or more instructions or code encoded on a non-transitory computer-readable medium 304. Non-transitory computer-readable medium 304 includes both computer storage medium and communication medium including any medium that facilitates transfer of a computer program from one place to another. A storage medium may be any available medium that can be accessed by a computer.

It will be appreciated that many further modifications and permutations of various aspects of the described embodiments are possible. Accordingly, the described aspects are intended to embrace all such alterations, modifications, and variations that fall within the spirit and scope of the appended claims.

Throughout this specification and the claims which follow, unless the context requires otherwise, the word "comprise", and variations such as "comprises" and "comprising", will be understood to imply the inclusion of a stated integer or step or group of integers or steps but not the exclusion of any other integer or step or group of integers or steps.

The reference in this specification to any prior publication (or information derived from it), or to any matter which is known, is not, and should not be taken as an acknowledgment or admission or any form of suggestion that that prior publication (or information derived from it) or known matter forms part of

the common general knowledge in the field of endeavor to which this specification relates.

**Claims:**

1. A computer-implemented method for optimizing performance of an energy dispatch system, comprising:
  - creating a digital twin representing the energy dispatch system, the digital twin having a current operational behavior of the energy dispatch system;
  - receiving future forecast data for a future time period;
  - identifying a set of initial setpoints for controlling the current operational behavior;
  - predicting, by the digital twin, one or more objective values based on the set of initial setpoints, current operational behavior and future forecast data; and
  - applying an optimization model to the set of initial setpoints, based on the one or more objective values, to produce an optimized set of setpoints for controlling the energy dispatch system.
2. The method of claim 1, wherein identifying the set of initial setpoints comprises identifying the set of initial setpoints from a plurality of setpoints, based on the future forecast data.
3. The method of claim 2, further comprising receiving a plurality of past forecast data corresponding to the future forecast data and a set of setpoints for each past forecast data, wherein identifying the set of initial setpoints comprises selecting the set of setpoints corresponding to a best past performance of the energy dispatch system.
4. The method of claim 3, wherein the plurality of past forecast data comprise one or more of meteorological data, load demand data.
5. The method of any one of claims 2 to 4, wherein the future forecast data and the past forecast data are forecast based on one or more of weather forecast, trends in historical data, and configuration of the energy dispatch system.

6. The method of any of claims 1 to 5, wherein the optimization model comprises one or more of particle swarm and stochastic programming.
7. The method of any of claims 1 to 6, further comprising operating the energy dispatch system according to the optimized set of setpoints.
8. The method of claim 7, comprising collecting operation data describing an operational behavior of the energy dispatch system for the future time period.
9. The method of claim 8, comprising updating the current operational behavior based on the operational behavior of the energy dispatch system for the future time period.
10. The method of claim 9, comprising updating the digital twin based on the current operational behavior.
11. A system for optimizing performance of an energy dispatch system, comprising:
  - a memory;
  - a training module configured to provide a digital twin representing the energy dispatch system, the digital twin having a current operational behavior of the energy dispatch system;
  - a receiving module for receiving future forecast data for a future time period;
  - a processor configured to identify a set of initial setpoints for controlling the current operational behavior;
  - a predicting module comprising the digital twin configured to predict one or more objective values based on the set of initial setpoints, current operational behavior and future forecast data; and
  - an optimization model configured to be applied to the set of initial setpoints to produce an optimized set of setpoints for controlling the energy dispatch system, based on the one or more objective values.

12. The system of claim 11, wherein the processor is configured to identify the set of initial setpoints by identifying the set of initial setpoints from a plurality of setpoints, based on the future forecast data.
13. The system of claim 12, wherein the processor is configured to receive a plurality of past forecast data corresponding to the future forecast data and a set of setpoints for each past forecast data, wherein the processor is configured to identify the set of initial setpoints by selecting the set of setpoints corresponding to a best past performance of the energy dispatch system.
14. The system of claim 13, wherein the future forecast data and the past forecast data each comprises one or more of meteorological data, load demand data, and information of the energy dispatch system.
15. The system of any one of claims 12 to 14, wherein the future forecast data and the past forecast data are forecast based on one or more of weather forecast, trends in historical data, and configuration of the energy dispatch system.
16. The system of any of claims 11 to 15, wherein the optimization model comprises one or more of particle swarm and stochastic programming.
17. The system of any of claims 11 to 16 further comprising an operating module for operating the energy dispatch system according to the optimized set of setpoints.
18. The system of claim 17, wherein the operating module is configured to collect operation data describing an operational behavior of the energy dispatch system for the future time period.
19. The system of claim 18, wherein the operating module is configured to update the current operational behavior based on the operational behavior of the energy dispatch system for the future time period.

20. The system of claim 19, wherein the training module is configured to update the digital twin based on the current operational behavior.