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Optimal Energy Management and MPC Strategies for Electrified RTG Cranes with Energy Storage Systems

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Abstract: This article presents a study of optimal control strategies for an energy storage system connected to a network of electrified Rubber Tyre Gantry (RTG) cranes. The study aims to design optimal control strategies for the power flows associated with the energy storage device, considering the highly volatile nature of RTG crane demand and difficulties in prediction. Deterministic optimal energy management controller and a Model Predictive Controller (MPC) are proposed as potentially suitable approaches to minimise the electric energy costs associated with the real-time electricity price and maximise the peak demand reduction, under given energy storage system parameters and network specifications. A specific case study is presented in to test the proposed optimal strategies and compares them to a set-point controller. The proposed models used in the study are validated using data collected from an instrumented RTG crane at the Port of Felixstowe, UK and are compared to a standard set-point controller. The results of the proposed control strategies show a significant reduction in the potential electricity costs and peak power demand from the RTG cranes.

Keywords: energy storage system; Rubber Tyre Gantry (RTG) crane; cost optimization; model predictive control; stochastic load; forecast

1. Introduction

An Energy Storage System (ESS) is a significant tool for a more energy efficient ecosystem and help to decrease environmental concerns [1,2]. In general, the objective of an ESS is to reduce the cost of electricity and avoid the need to upgrade the distribution network by shifting energy consumption from peak to valley periods [2]. ESS's are expected to be more frequently applied to a wide range of demand side applications. Recently, sea ports are moving towards replacing diesel RTG cranes [3,4], which move containers on a port platform and organise container storage in the yard area, with electric RTG cranes to reduce green gas emissions and improve energy efficiency [1–3]. In RTG crane system, most of electricity energy or fuel consumption comes from hoisting containers with different weights to several heights. Furthermore, the peak demand increases when the RTG crane moves heavier containers [5]. The details of RTG crane energy topology are discussed in Section 2. The shift to the use of electrified RTG cranes can reduce the costs for equipment repairs and maintenance by around 30% compared to diesel RTG cranes. However, as electricity demand on the ports' electrical distribution networks augments due to the electrification of RTG cranes, port operators will be forced to reinforce the network to meet this increased demand [3,4]. The traditional reinforcement solutions focus on upgrading or replacing existing electrical infrastructure such as cables and substations. This solution is effective but commercially expensive, which motivates the consideration of different ESSs technologies and control methods for supporting the power grid. In ports, ESS could play a vital role in reducing peak demand, the carbon gas emissions and Rubber Tyre Gantry (RTG) crane operation costs [4]. RTG crane load profiles have a highly volatile and stochastic behavior compared to other low and medium voltage loads including domestic customers. The nature of the electrified RTG crane load as well as the vague physically explanatory relationships between the crane load and exogenous variables such as temperature, wind speed and seasonality trends increase the challenges and difficulties in forecasting RTG crane load demand compared to low and medium voltage loads [5]. Difficulty in generating accurate crane load forecasts and the unpredictable load behaviour make it substantially more challenging to control and improve storage performance using forecast data. Most peak demand reduction strategies in the RTG crane and port applications equipped with ESS mainly focus on using a set-point control strategy to charge and discharge the storage based on the voltage, power or State of Charge (SoC) level. Furthermore, to the best of the author's knowledge, there are no studies which specifically consider the electrified RTG crane load forecast as an input to a control strategy.

In RTG crane systems, the majority of the energy consumption is produced by lifting containers to different heights. In order to increase the energy savings in electrified or diesel RTG crane systems, ESSs have been used for peak shaving during the lifting period by using recovered potential energy that has accrued during the lowering period and avoid dissipating energy through the dump resistors as heat [1,6–11]. In the literature, ESS control algorithms on an RTG crane system, which can be either a diesel or electrified crane, mainly focus on using conventional control strategies that use a reference value (set-point control) of power [1,9], SoC [7] or voltage [3,11] to store recovered potential energy and regenerate it during the lifting phase which helps to increase energy savings and reduce gas emissions. Table 1 summarises the peak reduction algorithms used in an RTG crane model produced by different authors along with their achievements and limitations. Table 1 shows that the majority of studies used set-point controller to increase energy saving of RTG crane systems and no research models use an MPC controller. Also, this table shows that there is limited literature on using different optimal control algorithms for increasing the energy efficiency of RTG cranes. To the best of the authors' knowledge, there are no studies on using the electricity bill cost in the objective function and load forecast profile to optimise the energy flow in RTG cranes network system by using optimal power management strategies or an MPC controller.

Pietrosanti et al. [1] present an optimal management strategy for RTG cranes with flywheel energy storage located at the DC side of the crane. The control strategy aims to find the optimal operation conditions for ESSs by charging the storage during the lowering mode and discharging it during the lifting mode, under uncertainties of the duration of RTG crane stochastic power loads [1]. Baalbergen et al. [12] developed diesel RTG crane systems equipped with battery storage. The authors in [12] presented a power management system which aims to increase the energy savings and minimise costs by regenerating the recovery energy. In this paper, we introduce an optimal peak shaving control strategy, which minimises the energy costs of an RTG crane system equipped with an ESS using real-time data. Unlike previous works that used the recovery energy from the lowering phase to minimise the cost and increase energy savings [1,12], the proposed optimal control in this paper aims to maintain an optimal charging and discharging schedule by using real-time electricity prices and RTG crane load data.

Furthermore, the focus of this paper is to minimise the peak demand and the energy costs for electrified RTG cranes by developing a model predictive control (MPC) strategy, to take into consideration the high level of uncertainty in the forecasts of RTG crane demand. This paper presents control algorithms using real-time data collected from electrified RTG cranes at the Port of Felixstowe, UK, to control the energy storage system located at the substation side of RTG crane network systems.

MPC controller has been used effectively within microgrids and low voltage network applications which involve high uncertainties in demand applications [2,13,14] to decrease the operation costs and increase the system efficiency. For example, Rowe et al. [2] presented a MPC controller that allows distribution network operators to control the energy storage systems on the low voltage network, which feeds domestic customers. The MPC controller integrates a deterministic forecast with the objective of maximising the peak reduction of the distribution network [2]. As in the study of Rowe et al., Oh et al. [13] developed an optimisation scheme for an islanded microgrid, using an MPC strategy [13]. The use of a multi-step MPC controller performed well for controlling diesel power sources and renewable energy sources with an ESS to minimise the energy cost operation [13]. Stochastic forecast loads with scenario-based MPC models of a microgrid system with Electric Vehicle (EV) integration have been presented in [14], where Ji et al. [14] developed a forecast model based on knowing of EVs charging schedules in advance, so they assume that they know when the electric vehicle needs charging. In case there are unknown charging requests, the MPC controller will apply the worst-case scenario and set the boundary at the greatest possible charging loads. In order to meet the demand scheduling of the grid, Xiong et al. [15] presented real-time MPC to optimise the power flow for a wind farm system equipped with an ESS. The objective function of the MPC controller contained three sub-objectives: firstly, it aimed to reduce the impact of a wind curtailment factor; secondly, to increase the ratio of generated wind power fed to the power grid; thirdly, to maintain the generation of power to the grid plan. The MPC controller successfully followed the power plan of the electrical power grid system [15]. In addition, other authors have used MPC controllers for large scale ESS located at wind power plants to improve the energy dispatchability [16]. The simulation results have shown that an ESS with model predictive control (MPC) can reduce the generation plan errors to meet the power grid needs by approximately 80% [16]. The work successfully shows the impact of the scheduling horizon on the generation plan error, where shorter scheduling horizons reduce the error in the generation plan by approximately 15% [16]. These sets of studies show the usefulness and capabilities of using MPC as an ESS control technique.

The literature has shown that an ESS can be beneficial for decreasing the energy costs and peak demand; accordingly, it is important to develop an optimal control strategy that maximises the advantages of the ESS and minimises the costs. An adequate power control strategy for electrified RTG cranes system equipped with ESS could be of great interest worldwide, as it will help ports around the world to decrease the electricity bill and gas emission. This is particularly important since RTG cranes are vital ingredients in the export and import goods processes. Aiming to fill the gap in the literature, this paper attempts to present and compare optimal energy management and MPC controllers for the control of ESS on the low voltage networks that feed electrified RTG cranes. The main objective of both controllers is presented to minimise electricity bills and peak demand. The optimisation algorithms in this paper will be tested to establish their appropriateness for electrified RTG cranes with ESS control by testing the control algorithms on data sets that have been collected over different RTG crane operation days. Therefore, the paper has three key new contributions that are listed as follows:

(1) We present an optimal energy management controller with the aim of minimising the energy costs and achieving the greatest peak demand reduction. This is contrast to the limited literature focused on using the regenerative power to increase energy savings in RTG crane systems.
(2) We predict half hourly electrified RTG crane power demand for one day-ahead and the forecast model is updated at each time step by including the real-time readings and the forecast error.
(3) Unlike previous studies, which often use the set-point controls to increase energy saving in an RTG crane system and neglect the forecast algorithm as inputs to improve the ESS efficiency, we present an MPC controller that helps to decrease the energy costs and achieve maximum possible peak reduction by using the RTG crane load forecast data as the main input parameter.

The remaining sections of this paper are organised as follows: Section 2 describes the topology of the ESS and RTG crane demand model. Section 3 introduces the RTG crane load demand and cost problem and the optimal controller. In Section 4, the model predictive controller is presented and discussed. The simulation results and analysis are discussed in Section 5. Finally, a summary of the work and conclusions are presented in Section 6.

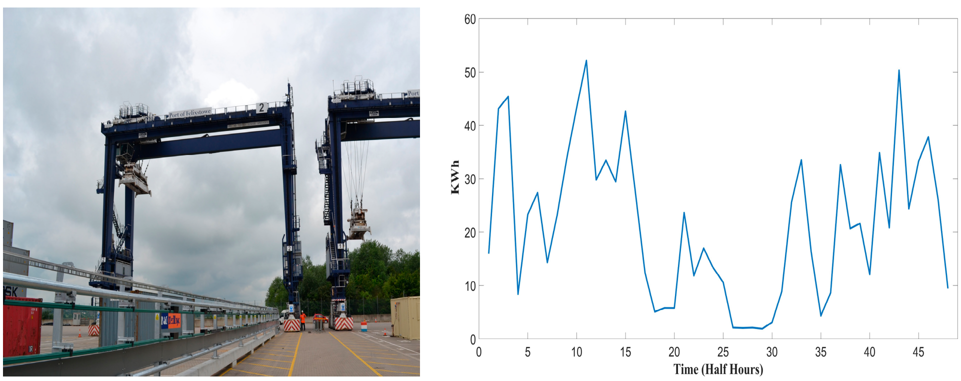
Table 1. Summary of the research for port cranes conducted by different authors along with their achievements and limitations.

Study	Domain	Control Technique	Achievement	Using Optimisation Algorithm
Zhao et al. [6]	Investigate the benefits of Hybrid-ESS for RTG cranes.	Closed-loop PI controller.	Increase the energy saving.	NO
Niu et al. [7]	Present a hybrid power source for an RTG crane with Active Front End.	Set-point control (SoC).	Improved battery storage efficiency.	NO
Ovrum and Bergh [8]	Investigate the benefits of hybrid power sources for ship cranes.	Optimal power management system.	Increase the energy saving and reduce gas emissions.	YES
Flynn et al. [9]	Investigate the benefits of flywheels energy storage for RTG cranes.	Set-point control (Power, voltage).	Increase the energy saving and reduce gas emissions.	NO
Pietrosanti et al. [1]	Investigate the benefits of ESS for RTG cranes.	Optimal power management system.	Increase the energy saving and reduce peak demand.	YES
Antonelli et al. [10]	Evaluate the energy flows for ESS equipped with RTG cranes.	Optimal energy management strategy.	Increase energy savings.	YES
Baalbergen et al. [12]	Investigate the benefits of storing regenerated energy.	Power management system based on energy savings point.	Increase energy savings.	YES
Kim and Sul [11]	Improve the performance of diesel RTG cranes with ESS.	Set-point control (Power, frequency).	Improve the energy efficiency of a RTG crane	NO
Alasali et al. [3]	Investigate the benefits of peak shaving for RTG cranes.	Set-point control (voltage).	Reduce peak demand.	NO

2. ESS and RTG Crane Demand model Topology

This section introduces the ESS and RTG crane model topology and addresses the RTG crane demand characteristics. The electrified RTG used in this work is shown in Figure 1a and it has been retrofitted to be powered by the distribution power network at the port via a conductor bar of length 217 m. This crane is manufactured by Shanghai Zhenhua Heavy Industries (ZPMC, Shanghai, China) and is currently used at the Port of Felixstowe [1], the numerical specifications of the RTG crane model is presented in Section 5.1. In addition, the half hourly RTG crane power demand $P_L(t)$ in Figure 1b shows a highly volatile and stochastic nature. The schematic diagram, shown in Figure 2, displays the power flow $P(t)$ from the energy sources (the power grid $P_g(t)$) and ESS $P_s(t)$ to the RTG crane load $P_L(t)$. The power flow diagram shows that the power grid $P_g(t)$ supplies all the required power consumption to operate both the RTG crane $P_g(t)$ and charge the ESS $P_s(t)$. In case the ESS starts discharging, the power grid $P_g(t)$ will only supply power of the RTG crane load $P_L(t)$ minus the discharged ESS power $P_s(t)$. The power flow can be described in the following equation [1,17]:

$$P_g(t) = P_L(t) - P_s(t), t\mathbb{R}^+. \quad (1)$$



(**a**) (**b**)

Figure 1. Crane system: (**a**) electrified RTG crane at the Port of Felixstowe; (**b**) an example of the actual electrified RTG crane demand for a specific day.

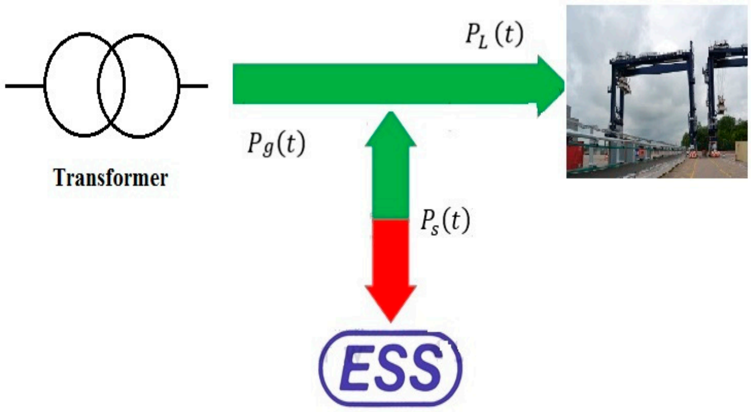


Figure 2. The power flow directions of the electrified RTG crane equipped with ESS.

2.1. The Energy Storage System

The primary energy source in the electrified RTG crane model is a substation (11 kV/415 V). The secondary side of the substation is connected to the DC bus in the crane system through a diode rectifier. In this paper, the Energy Storage System (ESS) is located at the low voltage side (415 V) in order to minimise the peak power and cost, as shown in Figure 3, at the substation side based on the real-time electricity price cost through the proposed optimal and Model Predictive Control (MPC) controller. As in [2,15,18], the ESS used in this paper is described by Equations (2)–(8):

$$E_s(t) = E_s(t-1) + \tilde{\eta}\left(\frac{P_s \triangle t}{ESS_{capacity}}\right). \tag{2}$$

The stored energy E_s in the ESS is calculated as in Equation (2), with the storage system operating under the following constraints:

- The energy limitation:

$$E_s{}^{min} \le E_s(t) \le E_s{}^{max}, \tag{3}$$

$$\triangle E_s{}^{min} \le \triangle E_s(t) \le \triangle E_s{}^{max}. \tag{4}$$

- The ESS power limitation

$$P_s{}^{min} \le P_s(t) \le P_s{}^{max}, \tag{5}$$

$$P_s(t) \ge \frac{E_s{}^{min}.ESS_{capacity} - E_s(t)}{\Delta t}, \tag{6}$$

$$P_s(t) \le \frac{E_s{}^{max}.ESS_{capacity} - E_s(t)}{\Delta t}. \tag{7}$$

- The ESS operation efficiency

$$\tilde{\eta} = \begin{cases} \tilde{\eta} \text{ if } \Delta E_s \ge 0; \text{charging period} \\ \frac{1}{\tilde{\eta}} \text{ if } \Delta E_s < 0; \text{discharging period} \end{cases}. \tag{8}$$

In this work, the control of the ESS aims to determine an optimal value of $P_s(t)$ in kW and the stored energy. The stored energy E_s is given as $P_s\Delta t$, during a period of time Δt. In this work, the energy stored in the ESS is increased and decreased, based on the RTG crane demand, $P_L(t)$, and the real-time electricity price, and is described as $\Delta E_s = E_s(t) - E_s(t-1)$. The stored energy in every time step ΔE_s, can be taken as a positive/negative change to present the increase/decrease of energy in the ESS. The negative value of Δ E_s means that the energy in the ESS has decreased (storage system in discharging mode) and when it is positive it means the energy in the ESS has increased (storage system in charging mode). Furthermore, the storage system is operated by constraints to maintain an upper limit on the stored energy ${E_s}^{max}$ and a lower limit on the stored energy ${E_s}^{min}$. Similarly, we define a maximum and minimum stored power, ${P_s}^{max}$ and ${P_s}^{min}$. These limitation rules are described in Equations (3)–(5), respectively. Also, the power limitation of the ESS are defined in Equations (6) and (7). The storage system algorithm considers the ESS efficiency [2,18] by combining the stored energy in each time step ΔE_s into a variable describing the storage efficiency $\tilde{\eta}$. When the stored energy is $\Delta E_s < 0$, the efficiency of the ESS is equal to $\frac{1}{\tilde{\eta}}$ and when ΔE_s is ≥ 0, the storage efficiency is $\tilde{\eta}$. Typically, the E_s quantity is defined as a value between ${E_s}^{min} = 0$ and ${E_s}^{max} = 1$; as in [1,2,18], the E_s can also be described as the State of Charge (SoC). The SoC at the end of each time step is updated based on the previous state of charge $\mathrm{SoC}(t-1)$, and the value of ESS charging or discharging energy ΔE_s.

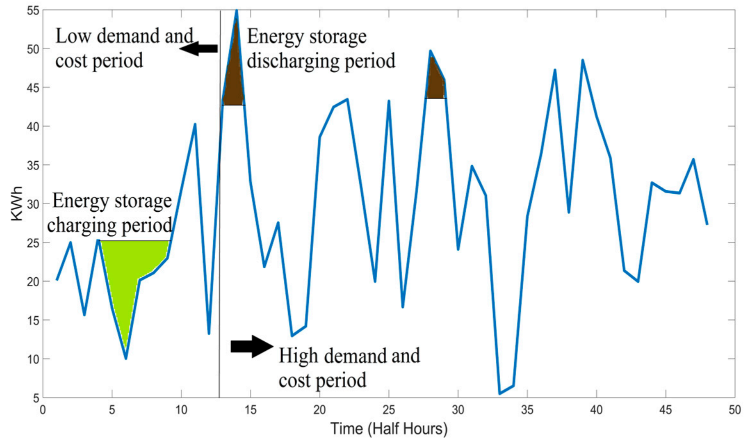


Figure 3. A specific example for peak shaving strategy.

2.2. The Electrified RTG Crane Load Demand

As described in Section 2, and shown in Figures 1 and 3, electrified RTG crane load profiles show a highly volatile and stochastic nature. Equation (1) describes the power flow in an RTG crane system equipped with an ESS located on the low voltage network. The objectives in this research is to minimise the peak demand $P_g(t)$ in the power distribution network by using the ESS, which is defined in Section 2.1. The volatile crane demand, $P_L(t)$, is equal to the summation of storage $P_s(t)$ and substation power $P_g(t)$, where this summation is used to generate a charge and discharge control decision for the ESS. In this paper, we present two optimisation controllers to control the ESS as follow:

(1) Optimal energy management controller: the real-time RTG crane demand and electricity price data are used to feed the optimal management control system. As indicated previously, the RTG crane load profile is highly stochastic; therefore, developing an optimal management control is difficult and challenging. This control will be described in Section 3.

(2) Model Predictive Control (MPC) controller: the MPC in this research is designed to use forecasted RTG crane load profile and electricity price data to find the optimal ESS output that minimise the peak load and cost. The MPC controller model will be described in Section 4. In this research, we extend the Artificial Neural Network (ANN) forecast model in [5] to create a rolling RTG crane power forecast as follows:

- Predict the half hourly electrified RTG crane power demand for one day-ahead.
- Update the forecast load profile in each time step by using the forecast error and real-time measurements.

As mentioned previously, the electrified RTG crane demand is challenging to predict due to the highly volatile nature of the load and there is no clear relation with physical exogenous variables such as temperature or seasonality [5]. However, the electrified RTG crane demand increases and decreases based on variables such as container gross weight, number of crane moves and the behaviour of the crane driver (human factor) [5]. These variables caused a wide range of forecast errors increasing the challenge of controlling the ESS. Figure 4 presents the daily mean absolute percentage error (MAPE) between the actual electrified RTG crane load and the load forecast [5], as described in Equation (9).

$$\mathrm{MAPE} = \frac{100}{24}\sum_{t=1}^{24}\frac{|\mathrm{P_L(t)} - \mathrm{P_f(t)}|}{|\mathrm{P_L(t)}|}. \tag{9}$$

where $\mathrm{P_L(t)}$ is the actual load value at time t, $\mathrm{P_f(t)}$ is the forecast load value at time t and t is the hourly time. In addition, the MAPE calculation is undefined when actual load is zero.

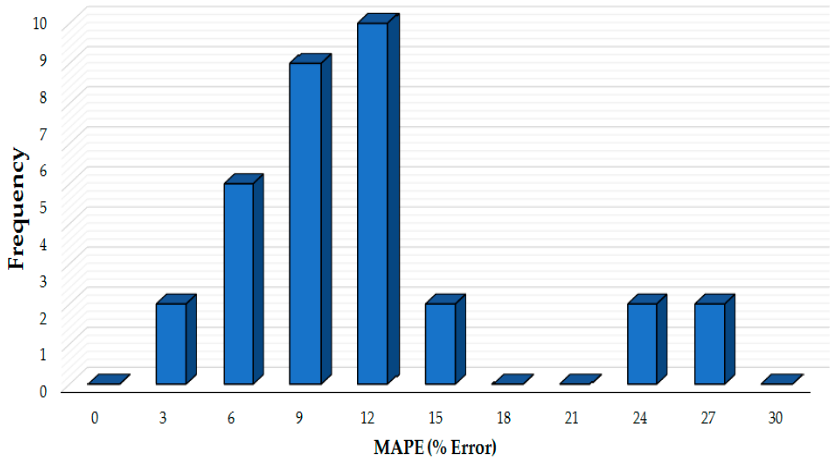


Figure 4. Histogram of daily mean absolute percentage error (MAPE) over 30 days in a histogram. The ANN forecasting methodology used to generate these daily MAPE values is presented in [5].

Figure 4 presents the daily MAPE error over 30 days of electrified RTG crane demand, the high number of occurrences is concentrated between 6% and 9%. Furthermore, the largest MAPE values (above 15%) are only repeated twice for MAPE errors equal to 24% and 27%. As seen in Figure 4, around 30% of the MAPE errors over one month are equal to 12% and around 80% of the MAPE values are under 12%. However, the MAPE results in Figure 4 show a wide range of values up to 30% which increase the challenging to develop a controller based on a load forecast profile. The electrified RTG crane demand has a highly volatile and stationary nature, without a clear relation with physical exogenous variables such as temperature or seasonality [5]. However, the correlation analysis in [5] showed that the container gross weight and number of crane moves are required to generate more accurate forecast model. The effect of human unpredictability on the demand shown comparing different crane electric demands for the same container gross weight [5]. In general, the crane operator decides the path for the crane move during the hoisting operation, where based on the site condition and container location they may choose to hoist the container through arc or oscillatory paths. The different move path means variations in the energy consumption for the same container weight which leads to less predictable demand.

3. Optimal Energy Management Controller

The optimal energy management controller can be designed for multiple objectives compared to the set-point algorithm [19,20] and find optimal solutions to control the designed model [21]. In this section, the objective of the optimal controller is to minimise the total cost C_{total} of using the electrified RTG crane (electricity bill), as described by Equation (10):

$$C_{total}(t) = \min\{(C(t)(E_L(t) - E_s(t)))^2\}. \tag{10}$$

where $C(t)$ represent the real-time electricity cost at the Port of Felixstowe, $E_s(t)$ is the store energy and $E_L(t)$ is the original electrified RTG crane demand at the current time step t. Figure 5 presents the proposed optimal management control loop for the electrified RTG crane system. The actual load profile of the crane, the real-time electricity price and the ESS measurement are fed to the controller in order to generate a control signal by minimising a cost function.

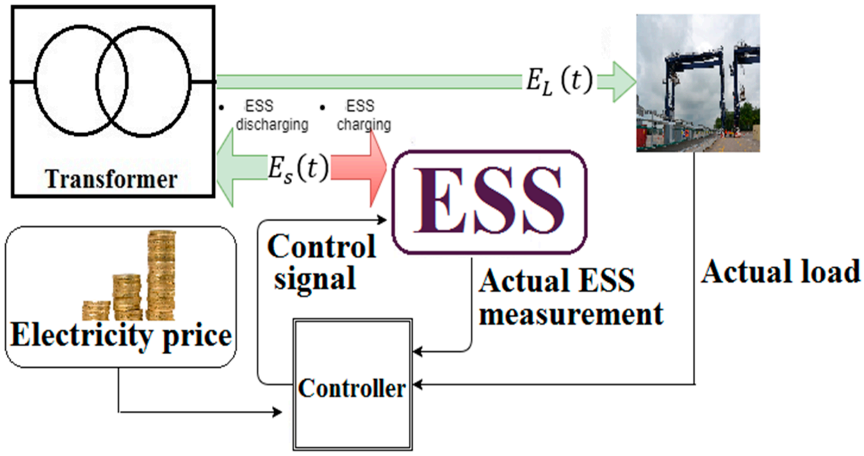


Figure 5. The schematic of the optimal energy management controller.

In order to minimise the energy cost and peak demand of RTG crane load for the daily time step, we minimize the cost function, defined by Equation (11), to find the optimal energy storage power:

$$\text{argmin}_{E_s(t)} \sum_{t=1}^{N} (C(t)(E_L(t) - E_s(t)))^2, \tag{11}$$

where t is the current time step, N is the daily time steps (N = 48, half-hours) and the controller is designed to compute the optimal control decision and apply it to the network system. The optimal energy management controller in Equation (11) takes into account the Equations (2)–(8) and will be subject to the constraint which are given by Equations (12)–(14):

$$C(t) = \begin{cases} C_{day} \text{ if } t \geq t_{set} \\ C_{night} \text{ if } t < t_{set} \end{cases}. \tag{12}$$

Equation (12) describes the electricity energy price at the Port of Felixstowe, where $t\{1, 2, \ldots, 48\}$. The electricity price during the day-time (C_{day}), between $t_{set} = 14$ and midnight, will be higher than the price during the rest of the day-time (C_{night}). This electricity tariff helps to shift the peak to a lower price period in order to minimise the cost and demand. In order to avoid superfluous charging periods and generation of new peak points, we define new constraints given by Equations (13) and (14):

$$P_L(t) - \tilde{\eta} P_s(t) \leq P_{ref} \tag{13}$$

$$\sum_{t=1}^{N} \left| \frac{1}{\tilde{\eta}} E_s(t) \right| \leq \sum_{t=1}^{N} |\tilde{\eta} E_s(t)|. \tag{14}$$

Equation (13) is used to maintain the power at the grid side under a set-point value during the ESS charging period, where the $P_s(t)$ value is negative and $\Delta E_s \geq 0$. The set-point value P_{ref} is found from a priori load data [1,22]. The limitation in Equation (14) is to make sure that the stored energy amount is more than or equal to the discharge amount of energy in the energy storage system.

In the optimal energy control model, the weighted sum of the electricity energy cost is calculated by the objective function, as in Equation (11). The optimal controller uses the peak shaving techniques to achieve the minimum cost and reduce peak demand by shifting demand from a high electricity price half hour to a low price half hour, as described in Equation (12). The peak shifting achieves the optimal solution by finding the optimal ESS output values which minimises a Cost function (electricity bill), as described in Equation (11). The ESS output calculates under constraint Equations (13) and (14) to avoid creating new peak points whilst charging the ESS especially since the optimal management control does not include the forecast load element. In Section 5, we will highlight and discuss the optimal management controller performance compared to a standard set-point controller. The set-point controller has been widely used in RTG cranes and different industrial applications and the set value is mainly developed using a priori load data [1,9,11]. Current energy storage control research studies have been initiated to inspect the benefits of load forecasting and planning control methods such as Model Predictive Control (MPC). As discussed previously, the highly volatile and stochastic nature of electrified RTG crane demand, and the difficulty in predicting the crane demand, make it more challenging to control the ESS using an MPC controller. The following section will present the MPC strategy and RTG crane load forecast problem.

4. Model Predictive Control (MPC) Controller

The MPC controller, sometimes known as the generalised predictive control and receding horizon control, is a time horizon optimisation model that determines a series of optimal control decisions over a specific future time period [23,24]. In the first control action, the MPC controller computes the decision for the first-time period based on the demand forecast and updates of other variables. In the subsequent time intervals the predictive control updates the forecast data and other operation variables in order to adjust the optimal control signal in every time step. This is repeated for all time steps [25,26]. Figure 6 presents the exemplified control scheme of the MPC system for an electrified RTG crane system with ESS. The crane measurement, updated demand forecast data, real-time electricity price and storage measurements are fed to the MPC controller in order to generate a control signal. The control decision uses the cost function in Equation (11) to minimise the electricity energy cost and peak demand. Figure 6 shows how the forecast model uses the real-time data (forecast error) to update the demand prediction at each time step. In this paper, the forecast model is designed to:

- Firstly, forecast the half hourly electrified RTG crane demand for 24 h ahead and generate a forecast load profile over t + 48.
- Secondly, calculate the forecast error at time t.
- Thirdly, regenerate the forecast load profile at each time step t for day ahead t + 48 by using the forecast error and actual measurements at time t, where the ANN forecast is rerun with the new observation.

As with the optimal energy management formulation, Equation (11) finds the optimal ESS energy that minimise the electricity bill (cost function). This cost formulation is subject to the constraints presented in Equations (2)–(8) and Equations (12)–(14) that aim to reduce peak demand and avoid creating a new demand peak. The MPC controller algorithm is described in Algorithm 1, where at the current time interval (t), the controller model gets the updated demand prediction data between t and t + i, where i is the forecast time step and $t + i \leq N$ and N is the one-day ahead forecast time (N = 48). Then the MPC controller calculates the optimal control decision by calculating the ESS energy in Equation (11) to minimize the cost function and implements the control signal to the network system. These steps are repeated at every time step t + 1 by updating the forecast data and other system variables and using the updated forecast data t + 1 + i to compute the control signal. The forecast model is designed to predict the load for one day ahead and then help the MPC to plan the control decision. After each time step the forecast model will use the actual data for this step and the forecast error to recalculate and update the forecast model. The MPC algorithm shows that the controller performance mainly depends on the accuracy of the prediction model [27,28]. As previously mentioned, the forecast data has been generated in this research by extending a prediction model developed in [5]. In addition, the forecast and the proposed control model in this work have been developed and solved using Matlab/Mathworks (R2016b, The MathWorks, Inc., Natick, Massachusetts, United States). The highly stochastic behavior of RTG crane demand and forecast error makes it more difficult and challenging to use an MPC control in an electrified RTG crane system. The literature has presented the MPC controller as vital for ESSs with volatile demands. The following section, discusses the performance of an MPC controller compared to set-point control and the optimal power management control.

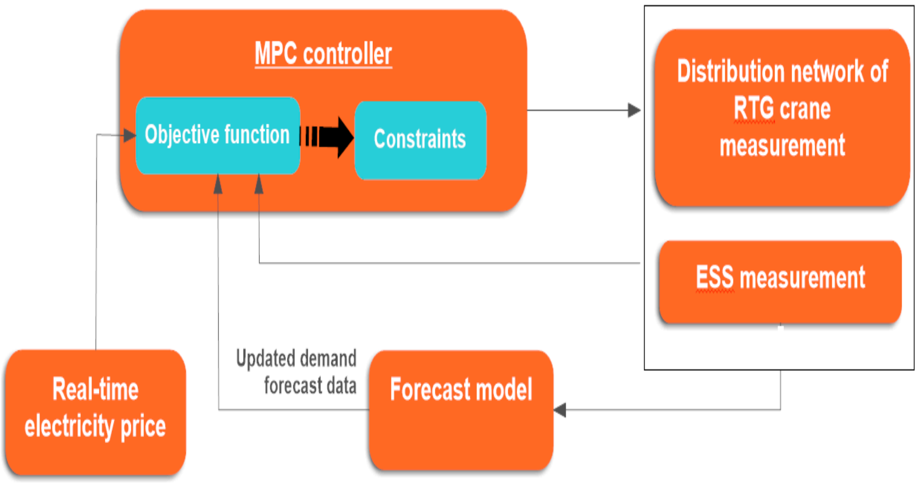


Figure 6. The scheme of model predictive control for electrified RTG crane system with ESS.

Algorithm 1: Basic concept for MPC for electrified RTG crane system model with ESS.

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1. Selecting the time horizon step and prediction horizon.
2. Determine the control objective and constraints.
3. Initialize: the crane, forecast data and ESS data.
4. For t = 1 to N (daily demand operation), do
    a. Solve optimal Equation (10),
       subject to:
        1. Equations (2)–(8).
        2. Equations (12)–(14).
        3. For (t = 1), the model computes the optimal solution based on the RTG crane demand prediction and initial data.
    b. Find the optimal signal for (t + 1) and apply it to the system.
    c. Update the forecast model for (t + 1) by regenerating the forecast load profile with the new observation and update the other system variables.
    d. Set t = t + 1,
5. Exit For loop.
6. An optimal solution is achieved for the electrified RTG crane system model with ESS for the specific day.
7. Repeat all steps for the next day.

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5. Results and Discussion

The proposed Model Predictive Control (MPC) and optimal management controller in this work was applied to an electrified RTG crane system model equipped with an ESS located at the low voltage side of the substation (power source). This section presents and discusses the system model parameters and results from the proposed optimal controller algorithms. First, the parameters of an electrified RTG crane model are presented; then, the optimal energy management controller and MPC controller are tested using a specific case study. Throughout this subsection, the proposed controllers are compared to a set-point control algorithm. The set-point controller has been discussed in the literature and is widely applied to crane systems [1,3,17]. In this work the set-point value has been selected using historical RTG crane demand data. The set-point controller compares the real-time RTG crane demand to the predetermined set-point value, then the storage controller makes a decision to charge the ESS if the demand value is under the set-point and discharge the storage if the RTG crane demand is above the set-point. The ESS will continue charging and discharging until it achieves the maximum set rate (E_s^{min} and E_s^{max}). Furthermore, in a set-point algorithm we take into account the real-time electricity price by encouraging the model to charge during the night and discharge during the day. The literature shows that the set-point algorithm is effective and simple, but is principally limited, as it takes the control decision without any future knowledge. The comparison of control algorithms we will present the peak demand and electricity cost reduction over a specific time of period for each controller.

5.1. Numerical Specifications

To verify the proposed optimal algorithms in this paper, the control algorithms have been tested on a simulation model of an electrified RTG crane with ESS. The main numerical parameters of the network of electrified RTG crane model are specified in Table 2 and Figure 7. The main network components of the electrified RTG crane systems have been modelled in MATALB/Simulink (R2016b, The MathWorks, Inc., Natick, Massachusetts, United States). This model has been updated and extended from an original model that was developed to study the energy savings in RTG cranes at the Port of Felixstowe to test the proposed optimal strategies [3,17]. The electrical network parameters and RTG crane demand data were collected from the Port of Felixstowe in the UK. In addition, the electrified RTG crane presented is three-phase load in this paper.

Table 2. Parameters of the electrified RTG crane network.

Section	Task	Components	Rating
Power source.	Generates the necessary energy to operate the electrified RTG crane.	Secondary transformer.	11 KV/415 V 1.6 MVA
Distribution	Provides the path to deliver the energy to the crane.	Cable 1 Cable 2 Cable 3 Cable 4 Conductor rail	0.0754 ohm/km 0.1240 ohm/km 0.3870 ohm/km 0.0991 ohm/km 0.0520 ohm/km
Loads	Drive and control the electrified RTG crane.	Three-phase demand	The actual and forecast demand from 21 to 25 May 2017.

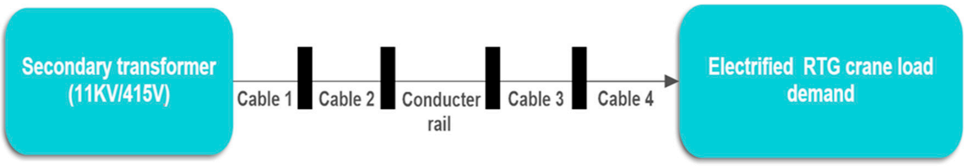

Figure 7. The schematic of an electrified RTG crane network system.

The electrified RTG crane energy demand was collected over 30 days and split into 25 historical days; the demand prediction was tested on the remaining 5 days. The actual and forecast of the electrified RTG crane demand are shown in Figure 8a and the real-time electricity price is displayed in Figure 8b, where the real-time electricity price data as provided by the Port of Felixstowe. The parameters and predefined data of the ESS, located at the low voltage side of the secondary substation, are presented in Section 5.2 (case study).

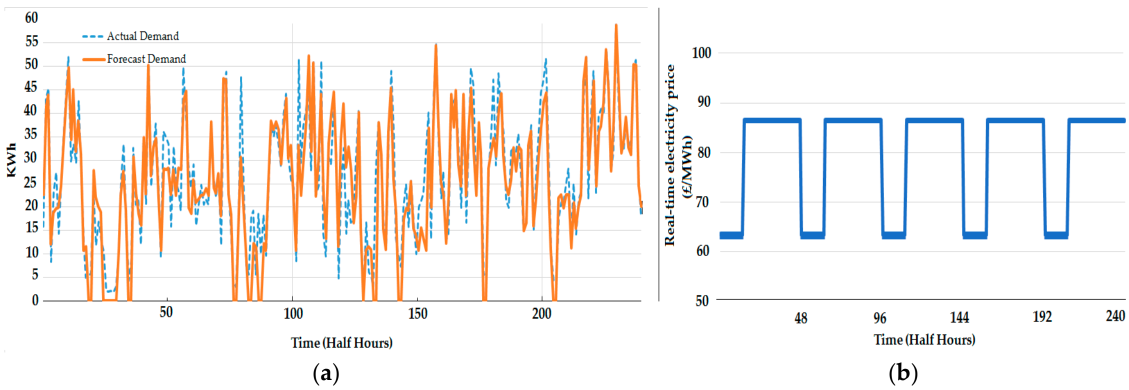

Figure 8. Profiles of (**a**) the actual and forecast electrified RTG crane demand; (**b**) the real-time electricity price.

Forecast Error

As previously mentioned, the forecast data is created using a ANN prediction model as described in [5]. However, in this paper, we modified the forecast model to predict the half hourly demand and the forecast model updated every time step by using the forecast error data. These modifications help to reduce the impact of forecast error on the model predictive control (MPC). Figure 9 shows that, in this paper, the highest number of forecast error instances are between −3.75 kWh and −0.27 kWh. The highest forecast error was +20.58 kWh and the maximum number of errors was around zero errors. According to the RTG crane demand analysis in [29] and the historical load data in this paper, the daily average energy demand is 600 kWh and the hourly demand usage is around 25 kWh, this means that the maximum forecast error value (+20.58 kWh) is very high compared to the average hourly RTG crane demand. Furthermore, the wide range of forecast errors between −12.45 kWh and +20.58 kWh and high forecast error values, as shown in Figure 9, increase the challenges and complexity of controlling the ESS through the MPC controller.

The forecast model in this paper has been used the actual load and forecast error for each time step to recalculate and update the forecast demand for the following 24 h, as discussed previously in Section 4. This updating helped the MPC controller to minimise the impact of forecast error on the control decision. Figure 10 presents the daily MAPE of forecast models with and without time step updating techniques over the 5 testing days. The results show, for the given data that updating techniques slightly reduced the forecast error and improved the prediction model performance. For example, on Day 3 the MAPE reduced by 4.9% from 27.3% to 22.4%. The minimum MAPE reduction was on Day 4 with only around 0.5% improvement.

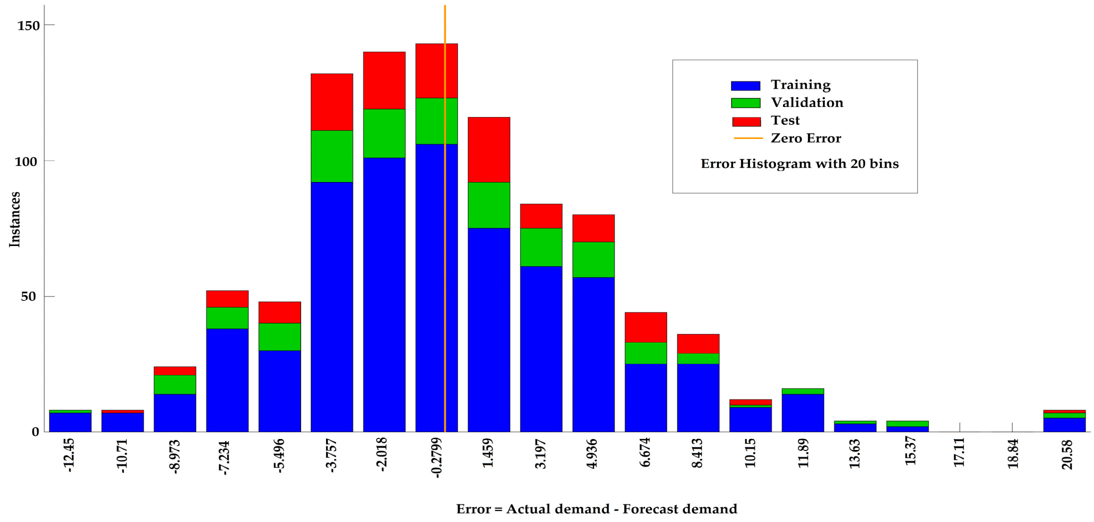

Figure 9. Illustration of the forecast error for training, validation and testing data in a histogram, where 70% of the historical data has been used as training, 13% as validation data and 17% as testing data (5 days testing).

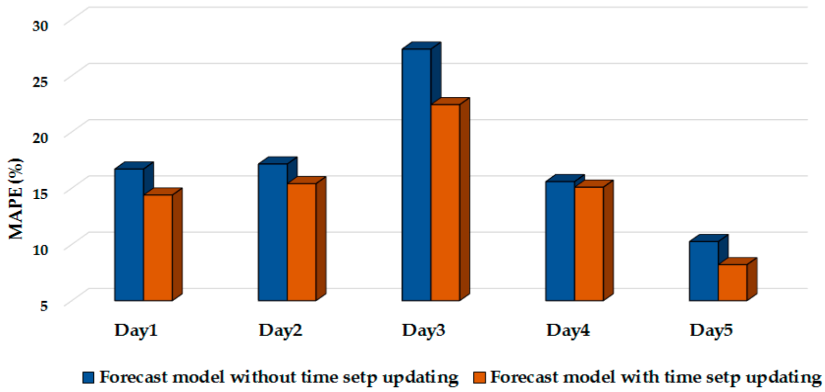

Figure 10. The daily MAPE for the RTG crane demand forecast model with and without time step updating method every time step based on the real-time readings and forecast errors.

5.2. Case Study: (A Spesifc RTG Crane Opeation Model Example)

In this section, the optimal control strategies (Optimal energy management and MPC controller) are implemented in the electrified RTG crane network system shown in Figures 5 and 6. The collected data for the electrified RTG crane has been divided into historical data (25 days) and testing data (5 days) is displayed in Figure 8a. In order to train and validate the forecast model, 80% of the historical data has been used as training data and 20% as validation data. To operate the electrified RTG crane network equipped with energy storage, Table 3 presents the Energy Storage System (ESS) parameters. The ESS parameters were applied in this case study to show the performance of the optimal control controllers compared to the set-point controller across the 5 days (testing period). The calculations of the stored energy ΔE_s for the RTG crane applications have been reported in [1], in this work, the discharge and charge rate of 150 kW has been used. In addition, this paper does not focus on the energy storage efficiency; therefore, $\tilde{\eta} = 1$. The optimisation horizon of power management and the MPC controllers is one day and the prediction horizon for MPC algorithm is 24 h with $\Delta t = 0.5$ h. The set-point is set at 36.5% of the greatest peak demand from the historical data using a typical set-point algorithm presented in the literature [2,22]; that aims to reduce the peak to an average ratio of around 4.5.

Table 3. Parameters of the Energy Storage System (ESS).

Parameter	Value
E_s^{min}	10 kWh
E_s^{max}	75 kWh
ΔE_s^{min}, ΔE_s^{max}	±75 kWh

The simulation results for this example showing the comparison of three different control strategies are presented in Figures 11 and 12. The MPC controller outperforms both the optimal management controller and the set-point control: the MPC controller achieves a 28.9% demand reduction; optimal energy management 25.3% and set-point control 22.09% peak demand reduction, where the peak reduction is calculated based on the power reference value. In addition, as the MPC controller uses load forecast data to decide on a charging and discharging schedule, the ESS charges to full rate during the valley demand values and during the lower electricity price rate. The optimal function and constraint equations in this paper minimise the risk of creating a new peak demand during charging mode for the given data set (testing period data). In contrast, the set-point controller has presented new peaks point at the 4th and 6th half hours and the set-point load curve is volatile and non-smooth.

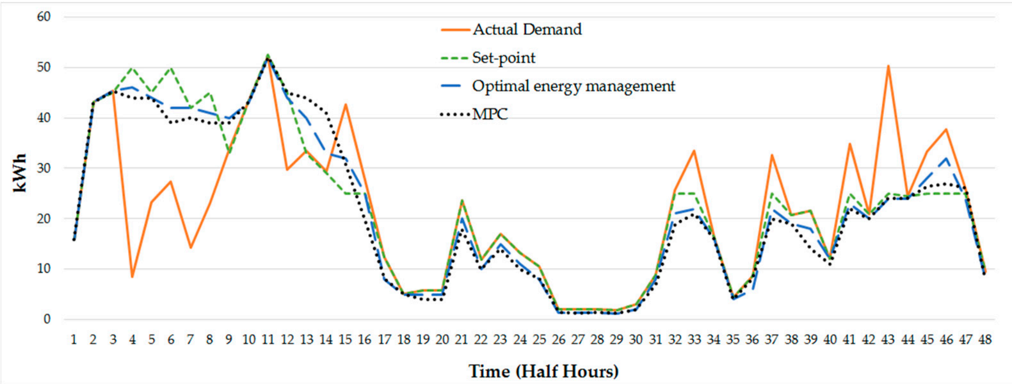

Figure 11. Specific example results: The actual demand, optimal energy management controller results and MPC controller results for one day.

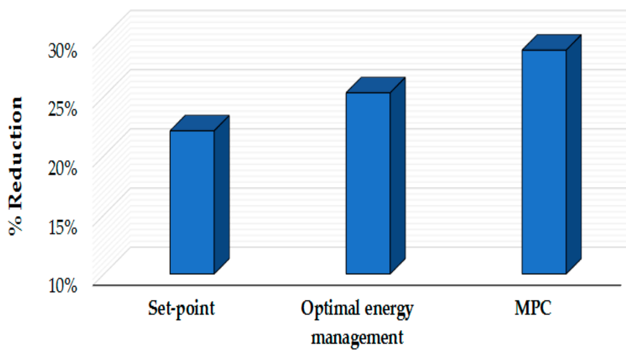

Figure 12. The percentage of demand reduction results for a specific case study.

βThe cost function used in this paper for the proposed MPC and optimal management controllers create substantial reduction in peak demand of the electrified RTG crane. This peak reduction is presented in Table 4 by showing the percentage of time that the power grid $P_g(t)$ is feeding the network more than 150, 200 and 250 kW. The proposed Model Predictive Control (MPC) has favourable results compared to other control strategies in this paper. The proposed MPC controller outperforms the set-point and optimal management controller and limits the peak demand over the testing period. The peak reduction achieved in this research reduces the stress on the port substation. In addition, the peak reduction shows a significant opportunity to decrease electricity bills.

Table 4. Parameters of the Energy Storage System (ESS).

Scenario	Percentage of Time over 150 kW	Percentage of Time over 200 kW	Percentage of Time over 250 kW
No ESS	4.467%	2.991%	0.803%
Set-point control	3.774%	0.827%	0.184%
Optimal management	2.231%	0.705%	0.130%
MPC	1.825%	0.665%	0.122%

In this paper, the cost function aimed to reduce the electricity energy cost using a demand shaving strategy. Figure 13 presented the shifted energy demand from the high to low electricity price period over the five days. The shifted energy using the MPC controller achieved ranges of 130 to 146 kWh, while the optimal energy management scheme produced ranges from 118 to 140 kWh and set-point control ranges from 85 to 110 kWh. This indicates a daily average shifted energy of 138.8, 124.4 and 98.6 kWh for MPC, optimal energy management and set-point controllers, respectively. Additionally, if this daily average energy could be shifted, cost savings in the port electricity bill could be achieved. According to RTG crane demand analysis in [27] and the historical load data in this paper, the daily average energy demand is 600 kWh, so shaving 50.52 MWh yearly will result in electricity bill savings of £1163.6 every year, when using an MPC controller. According to information provided by technical staff at the Port of Felixstowe and with a daily average energy consumed by electrified RTG crane of 600 kWh, the annual electricity energy cost is around £16190.17, the MPC saving will result in an annual electricity bill saving of 7.18%. Table 5 presents the annual cost saving in all the proposed control algorithms.

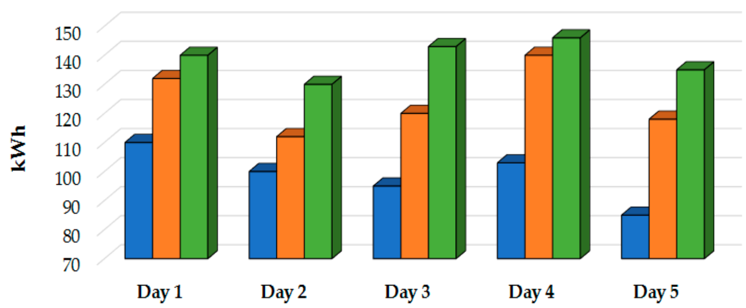

Figure 13. The daily energy demand shifted from the high to lower price electricity rate.

Although MPC produces the best peak reduction, it has the most computationally expensive and high precision requirements for designing and controlling the energy storage system. On the other hand, the set-point controller is the worst at reducing peaks but is inexpensive and very easy to implement where it is widely used in industrial applications and energy storage systems.

Table 5. The annual cost saving and percentage of cost savings to the annual electricity bill by using peak saving techniques for electrified RTG crane equipped with an energy storage system.

Scenario	Annual Cost Saving	Percentage of Cost Saving
Set-point control	£826.59	5.10%
Optimal management	£1042.88	6.44%
MPC	£1163.60	7.18%

6. Conclusions

The highly volatile and stochastic nature of electrified RTG crane demand with no clear horizon patterns and high uncertainty levels in the crane load forecast increase the challenge of predicting and controlling the RTG crane demand. Therefore, an advanced control strategy is required to minimise the impact of forecast error and non-smooth load behaviour. In this paper, optimal energy management and MPC strategies have been developed and implemented to improve the economic performance of the electrified RTG crane network equipped with an ESS by minimising the electricity energy bill and peak demand. The optimal cost function has been used together with the real-time electricity price, power grid specifications and energy storage system parameters. The example case study results show that the proposed optimal strategies are effective at reducing the peak demand and electricity energy cost compared to set-point control. In particular, the MPC controller, for the given RTG crane data, has favourable results and outperforms the optimal energy controller and set-point control. In line with the benefits of peak demand reduction and electricity cost savings it could also potentially minimise the stress on the electrical infrastructure at the port and avoid the need to upgrade or build a new substation.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviation are used in this paper

RTG	Rubber Tyre Gantry
MPC	Model Predictive Control
ESS	Energy Storage System
SoC	State of Charge
$P_L(t)$	Power demand (RTG crane)
$P_g(t)$	Power grid at time t
$P_s(t)$	Power energy storage at time t
$E_s(t)$	Energy stored in the ESS at time t
ΔE_s	The stored energy in the ESS between time t and $t - 1$
${E_s}^{max}$	Greatest stored energy
${E_s}^{min}$	Lowest stored energy
${P_s}^{max}$	The maximum stored power in the ESS
${P_s}^{min}$	The minimum stored power in the ESS
$\widetilde{\eta}$	The energy storage efficiency
C_{total}	Total energy cost
$C(t)$	Represent the real-time electricity cost at Port of Felixstowe
$E_L(t)$	The electrified RTG crane demand at time t
C_{day}	The electricity price during day time (07:00 to 24:00)
C_{night}	The electricity price during night time (24:00 to 7:00)
P_{ref}	Set-point power value

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