A Model Predictive Control-Based Energy Management Scheme for Hybrid Storage System in Islanded Microgrids

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ABSTRACT Model predictive control (MPC) facilitates online optimal resource scheduling in electrical networks, thermal systems, water networks, process industry to name a few. In electrical systems, the capability of MPC can be used not only to minimise operating costs but also to improve renewable energy utilisation and energy storage system degradation. This work assesses the application of MPC for energy management in an islanded microgrid with PV generation and hybrid storage system composed of battery, supercapacitor and regenerative fuel cell. The objective is to improve the utilisation of renewable generation, the operational efficiency of the microgrid and the reduction in rate of degradation of storage systems. The improvements in energy scheduling, achieved with MPC, are highlighted through comparison with a heuristic based method, like Fuzzy inference. Simulated behaviour of an islanded microgrid with the MPC and fuzzy based energy management schemes will be studied for the same. Apart from this, the study also carries out an analysis of the computational demand resulting from the use of MPC in the energy management stage. It is concluded that, compared to heuristic methods, MPC ensures improved performance in an islanded microgrid.

INDEX TERMS Energy management, model predictive control, fuzzy systems, energy storage systems, degradation reduction, islanded microgrid.

I. INTRODUCTION

Renewable energy sources (RES) are increasingly integrated into electric grids to replace the fossil fuel based sources. Though RES provide a clean energy alternative, they are non-dispatchable and intermittent in nature. These characteristics of RES have resulted in issues pertaining to stability, voltage regulation and power quality in the grids [1], [2]. The addition of energy storage systems (ESS), in the grid, is currently considered to overcome these issues and aid the increased integration of RES [3], [4].

A single type of ESS cannot provide an effective solution to the different problems arising from RES integration. The ESS have different physical attributes which are suited for different scenarios and a hybrid combination provides an effective solution. The hybrid ESS also enables optimal

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sizing of the different ESS [5]. In this context, hybrid ESS combination of high power and energy density storages are widely used in electrical systems [6]. The high energy density ESS are capable of storing large amount of energy but have slow response time due to physical constraints. These include Pumped hydro storage, Fuel cells (FC)-electrolyser systems (regenerative FC), batteries. These ESS provide dispatchable energy reserves that allows deferral of RES power consumption and facilitates energy arbitrage [4], [7]. The high power density ESS can provide or absorb large amount of power, albeit for a short duration due to their lower energy capacity. These include supercapacitors (SC), flywheel to name a few. These ESS have fast response capability which makes them suited for ensuring stability and power quality (voltage, frequency regulation) in grid [3], [8].

The RES integration has resulted in a shift from centralised to distributed generation [9]. This has enabled the concept of microgrids which can manage locally, the energy from

RES and load demand by forming subsections in the larger grid. The microgrids are capable of operating in grid connected or islanded mode. The islanded mode was traditionally employed during fault events in the main grid or in isolated areas, where drawing long lines connecting to main grid is physically and economically not viable. Traditionally, intentional islanding was not allowed to avert any risk to maintenance operations [10]. However, new standards like IEEE Std 1547.4 [11] provide guidelines for intentional islanding operation.

The microgrid control is achieved using a hierarchical scheme, with a lower-level power and a higher-level energy management stage [12]. The two stages are differentiated by the functions they carry out and the time scales in which they operate. The power management stage ensures real-time stable operation of microgrid under disturbances (variations in load or generation) and the power quality. This stage is characterised by small sampling times (*ms-s*) and fast control actions. The energy management stage is responsible for managing the energy among the different units (ESS) in the microgrid such that the operation of microgrid is optimised based on a pre-defined criteria. The sampling times of this stage tend to be larger (minutes - hours) and control actions are slower, in comparison to the power management stage [13], [14]. The functionalities and sampling times at each level in the hierarchical control scheme is shown in Fig.1. The inputs to each stage and flow of control action is also highlighted in the above figure.
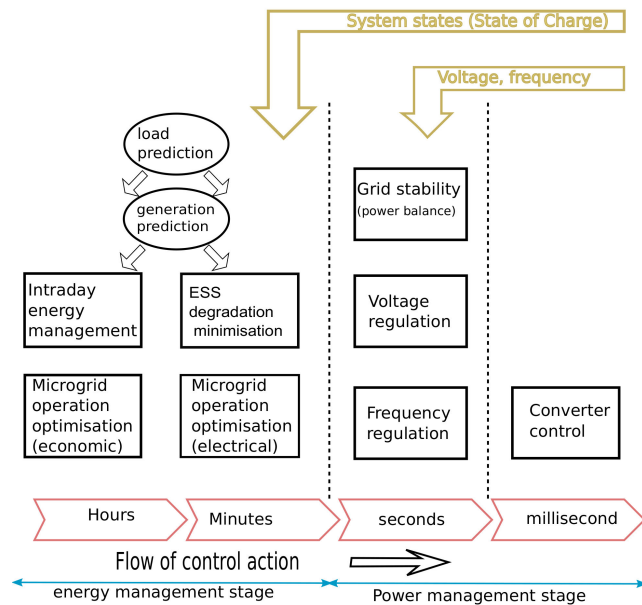

FIGURE 1. Control architecture for renewable energy based microgrid employing ESS.

The focus of this work is on the energy management stage. The decision making at the energy management level, in microgrids, is carried out either heuristically (rule based [15], [16], fuzzy inference methods [17]) or analytically

(non-heuristically) using optimisation based techniques [18]–[26]. The decision making in heuristic methods are typically based on some deterministic rules and do not require explicit modelling of the system. As a result, the decision making process is not computationally intensive. The analytical methods, on the other hand, rely on system models, forecast of generation and load profiles in its decision making. The decision making in analytical methods is achieved by solving an optimisation problem. This guarantees optimality of the solution unlike heuristic methods, which also require a prior in depth understanding of the system behaviour to formulate optimal rules. As the analytical methods makes decisions by solving an optimisation problem, the required, ideal, system behaviour can be defined implicitly through the cost function of the optimisation problem. In comparison, the heuristic methods require that the required system behaviour need to be defined explicitly. Finally, analytical methods allow an easy incorporation of forecast information in the decision making process, through proper formulation of the optimisation problem. The forecast provides more insight into future system behaviour and enables better decision making. However, in heuristic methods incorporating forecast information is tedious. The rules for decision making in heuristic methods, when using forecast data, need to be stated explicitly. In this scenario, integrating the forecast information leads to complex rules formulation and requires a comprehensive, prior, understanding of system behaviour.

Analytical methods can be implemented either offline [18]–[20] or online using techniques like model predictive control (MPC) [21]–[27]. The offline methods are usually employed when the system under consideration is large, distributed [18] or when complex non-linear optimisation problems have to be solved [19], [20]. In either case, the computation time can be very large which makes an online implementation infeasible. The offline nature of implementation can result in the decisions being farther away from optimum, as the actual system behaviour (generation, load) can deviate from that considered during the decision making process (forecast). In online methods, like MPC, the decisions at any instant are made using the current system state and updated forecast at that time. This utilisation of current system value for decision making ensure that performance with online methods are closer to the optimum. In smaller systems like microgrids, due to the limited number of decision variables online methods, like MPC, can be easily implemented.

Energy scheduling in electrical system with MPC has been explored before. In [22], MPC was used in battery management for smoothing the output from a wind power plant. In [26], MPC was used for managing a regenerative FC in a microgrid with PV and wind power to increase the operational efficiency of FC system. In [23], the MPC was used to improve economic benefit from energy arbitrage in a microgrid with battery storage. The works in [21], [25] also use MPC for energy arbitrage. In [21], a microgrid with tri-hybrid storage was considered whereas in [25], thermal storage was also considered. In [24], MPC was applied to an

isolated power grid with battery storage for reducing operating costs of the grid. Finally, the work in [27] uses MPC to improve demand response capabilities in a microgrid to improve the PV power utilisation. Recent works pertaining to application of MPC in electric systems, have focussed on implementing them in large scale networks, using online distributed optimisation techniques to reduce operational costs [28], [29].

The previous works focussed mainly on utilising MPC for grid connected systems, with the objective of economic optimisation (operating cost or energy arbitrage). However, the capability of the MPC can be extended beyond this. Islanded microgrids present an interesting and relevant application for MPC based energy management, considering the increasing probability of such operation in future grids. The management of islanded microgrid is challenging due to the lack of an infinite energy reservoir in the form of main grid, to handle imbalance power that cannot be catered by the ESS and load. This requires power curtailment capability and dispatchable generators to ensure reliable operation. Islanded microgrids also require hybrid ESS of high energy and power density to sustain the islanded operation. In this context, MPC can be utilised in islanded microgrids beyond the domain of economic optimisation. The availability of forecast information can be used for reducing degradation in ESS by altering their charge discharge cycle. The forecast information can also be used for increasing the utilisation of renewable source by reducing power curtailment while ensuring uninterrupted operation.

Recently machine learning (ML) based approaches, like Q-learning, have been employed for scheduling in microgrids [30], [31]. These methods utilise reinforcement learning techniques [32] to train an ML system so as to facilitate optimal battery scheduling in microgrids. The decision making with ML system can be considered akin to heuristic methods. These methods do not solve an analytical equation for its decision making. Instead, they automatically develop an in-depth understanding of the optimal system behaviour in the training process that aids the decision making process. However, ML system uses only current system state for its decision making [30], [31]. Incorporating forecast information, which is beneficial for reducing ESS degradation and increased utilisation of renewable sources, can lead to complex and computationally intensive training process. In this context, analytical methods that enable easy integration of forecast information in its decision making can perform better when the objective of ESS degradation minimisation and maximising RES utilisation is considered.

Considering the above mentioned reasons, the main objective of this paper will be to develop an MPC based energy management system for an islanded microgrid. The islanded grid will have RES generation with PV system, dispatchable generation and hybrid ESS. The proposed MPC will manage the energy among the different ESS to minimise their degradation, increase the consumption of RES power in the microgrid and improve operational efficiency in microgrid.

In order to demonstrate the improvement with MPC scheduling, the work also carries out a comparative analysis with a fuzzy based energy scheduling scheme. The computational demand arising from the utilisation of MPC at energy management stage will be assessed. Therefore, the contributions of this work involve developing an MPC based energy management system that a) ensures uninterrupted operation of an autonomous islanded microgrid with ability for RES power curtailment b) manages energy among the hybrid ESS such that degradation of ESS is reduced and operating efficiency is maximised c) manages ESS and dispatchable generators to ensure increased utilisation of renewable generation and d) provides improved performance over multiple objectives compared to heuristic scheduling schemes. As far as the authors knowledge goes such an application of MPC in islanded microgrids, to achieve the above mentioned outcomes, have not been proposed before. A deterministic MPC, where the future generation and load demand is known with certainty, will be used in this work, demonstrate the above outcomes.

The rest of the paper is organised as follows. Section II provides an overview of the islanded microgrid under consideration. Section III provides an overview of the MPC and Fuzzy inference based energy management schemes considered in this work and their formulation. Section IV presents the results of MPC scheduling in islanded microgrid and its comparison with the fuzzy inference scheme. Finally the work is concluded in Section V.

II. SYSTEM DESCRIPTION

The DC microgrid under consideration for the unit commitment problem is shown in Fig.2. This is an aggregated representation of the system. The microgrid has RES generation from PV arrays, dispatchable generators and hybrid ESS comprising of batteries, regenerative FC and SC. Considering the islanded operation, to ensure reliable grid functioning, dispatchable sources in the form of fast acting generating units is considered here. Load following reserves capable of fast responses and very little start up time like, diesel or gas engine generators will be considered as dispatchable units [33].

It should be noted that in the islanded grid two ESS with high energy density, battery and regenerative FC, are used. This is because in islanded operation, due to the absence of the main grid, a large storage capacity is needed to ensure maximum utilisation of the excess PV power generated. The battery is a system that stores energy internally (in the form of chemical energy) and in order to store large amount of energy, a large capacity battery should be used. This is not economically beneficial; as the battery has very high storage costs [34]. This means that larger the battery capacity, larger the capital investment needed. In comparison, the FC system stores energy externally in the form of hydrogen (in tanks). As a result, increasing energy storage capability of FC system is not expensive. This is confirmed by the fact that the storage costs of an FC system, with hydrogen, is 0.005 times the
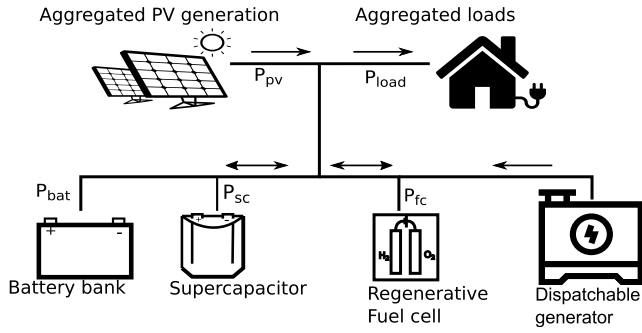
FIGURE 2. Schematic of the proposed microgrid under consideration.

battery's cost [34]. However, as mentioned before the regenerative FC suffers from poor operational efficiency. Therefore, both battery and regenerative FC is considered in the islanded microgrid, as a trade off, considering economic factors and operational efficiency.

A. ESS
The tri-hybrid ESS considered here comprises of both high power and high energy density ESS. The SC is the high power density ESS, whereas the battery and regenerative FC form the high energy density ESS. The SC provides a degree of inertia to the system through fast response to sudden power imbalances, thus arresting the large deviations in system parameters (voltage, frequency). In this context, the SC operation can be considered analogous to the inertial response from conventional synchronous generator. The battery and regenerative FC system follow the imbalance power in the system (difference of renewable generation and load) ensuring long term energy balance.

The operation of SC is mostly controlled by the low-level controllers (power management stage), tasked with maintaining the stability of the grid. The energy management level will ensure that sufficient energy reserves are maintained in the SC at any instant so that it can respond to unexpected events in the grid. The battery and regenerative FC will be managed by the energy management stage.

A discrete-time model of the ESS showing the evolution of stored energy during ESS operation will be used here. This simple ESS model using State of Charge (SOC) for battery, SC and Level of hydrogen (LOH) for regenerative FC is given by

$$x_\alpha(i+1) = x_\alpha(i) - \frac{T_s}{C_\alpha} \cdot p_\alpha(i) \tag{1}$$

where $x = \{SOC, LOH\}, \alpha = \{bat, SC, FC\}$, T_s is the sampling time, $p_\alpha(i)$ is the power set point and C_α is the capacity of respective ESS. The above equation does not account for the effect of the interfacing converters and the round cycle efficiency of the ESS. The converters usually have high efficiency ($>95\%$). Nevertheless, ESS like the FC have poor round cycle efficiency ($\sim50\%$) [8] which cannot be captured effectively with (1). Under such a scenario,

hybrid models accounting for ESS efficiency can provide a better representation of the ESS behaviour. This model is given by

$$x_\alpha(i+1) = \begin{cases} x_\alpha(i) - \dfrac{T_s \cdot \eta_\alpha}{C_\alpha} \cdot p_\alpha(i) & \text{if } p_\alpha \leq 0 \\ x_\alpha(i) - \dfrac{T_s}{\eta_\alpha \cdot C_\alpha} \cdot p_\alpha(i) & \text{if } p_\alpha > 0 \end{cases} \tag{2}$$

where η_α is a combination of the power converter and round cycle efficiency of the ESS.

B. PV SYSTEM
The PV system is considered as the renewable energy source in the islanded microgrid. One of the objective of the energy management system is to ensure that there is maximum utilisation of the PV power possible. The widely used method in PV systems to ensure that maximum power (for a particular irradiation level) is generated from the PV array, is the maximum power point tracking (MPPT) strategy [35]. The MPPT is implemented at the PV converter control, thus forming part of the low level control system. This ensures that the PV array is generating the maximum power (p_{pvm}) possible at any instant. In islanded operation, using MPPT in the PV systems can lead to instances where the load and ESS may not be able to meet the maximum PV power generated. This requires that the power is curtailed to ensure reliable grid operation. This curtailment can be implemented using the modified MPPT strategy with constant power generation (CPG) [36] capability. In this method, the PV array generates maximum power in normal condition but if the power generated cannot be met by the load or ESS the PV array output is curtailed to a constant power value. The PV array output (p_{pv}) in the MPPT with CPG scheme is given by

$$p_{pv} = \begin{cases} p_{pvm} & \text{No curtailement} \\ p_{pvm} - p_{curr} & \text{Under power curtailemt} \end{cases} \tag{3}$$

where p_{curr} is the amount of power to be curtailed by the PV system. The decision on the amount of p_{curr} will be made by the energy scheduling system.

In this work, the PV system and the load will be emulated using the data measured from a test case microgrid from Lindenberg, Germany [37]. The data is available for one year. The value of maximum PV power (p_{pvm}) that can be generated by the arrays for the irradiation levels occurring in the year is obtained from this data. A detailed discussion on the MPPT or MPPT with CPG strategies are not provided in this work, as they have been widely researched [35], [36] and is beyond the scope of this work. The objective of this work will be determining an optimal value of p_{curr}.

C. GRID
The grid is modelled, under all instances, as a static system using power balance equation given by:

$$p_{sc}(i) + p_{bat}(i) + p_{fc}(i) + p_{pvm}(i) + p_{gen}(i)$$
$$- p_{load}(i) - p_{curr}(i) = 0 \tag{4}$$

where p_{bat}, p_{sc}, p_{fc} are the power set points for the ESS while p_{load} is the load demand and p_{gen} is the set point for dispatchable generation unit.

A detailed modelling of dispatchable generation unit is not done here, especially with regards to ramping rate limitation. Instead it is considered only as a decision variable in this problem. The reason behind the same is that the dispatchable generating unit considered here is a fast acting system (as mentioned before) which is brought into operation quickly with minimum delay. The power imbalances created by the small delay in deployment will be compensated by the SC under the control action generated by the low level controller.

III. ENERGY MANAGEMENT SYSTEM
A. MODEL PREDICTIVE CONTROL BASED ENERGY SCHEDULING
In this work the receding horizon MPC is considered. In the MPC framework, at any instant k, the state of hybrid ESS, the sampled value of generation and load demand at that instant and their forecast for N points into the future $(k+1, k+2, \ldots, k+N)$ are given as inputs. This window for which the forecast is provided is called the prediction horizon. The predicted values are then utilised to evaluate how the system state evolves for different set points in the horizon. The set points that define the optimal trajectory, based on some optimisation problem will then be generated. Considering the size of prediction horizon, N + 1 set points will be generated at any sampling instant k. These set points are defined as, $\mathbf{u}_{0|k}, \mathbf{u}_{1|k}, \mathbf{u}_{2|k} \ldots \mathbf{u}_{N|k}$ where $\mathbf{u}_{i|k} = \mathbf{u}(k+i) \forall i = 0, 1, \ldots N$. Among the N + 1 set points the first one, $\mathbf{u}_{0|k}$, will be applied to the system. This process will be repeated at every sampling instance, thus allowing for the MPC to make decisions based on current system state and ensure some feedback [38].

The entire process of MPC scheduling discussed above is schematically represented by Fig.3. In the islanded microgrid, considered in this work, the input to the MPC will be sampled state of all ESS, PV generation and load demand values at the instant k. Along with the sampled values, the forecast of PV and load demand for the prediction window will also be provided as input. The output from the MPC will be the set points for the ESS converters, the dispatchable generator and the PV power curtailment value. The $\mathbf{u}_{0|k}$ comprises of all the above mentioned outputs.

Finally, it should be noted that the application of MPC can also be extended to multi-carrier system where, as the name suggests, multiple carriers are used to handle energy like electric, gas to name a few. MPC can used in the energy management of these systems as well [39], [40]. The formulation of the optimisation problem used in the MPC is discussed next.

B. COST FUNCTION
In this work MPC is tasked with maximising operating efficiency, renewable energy utilisation and minimising ESS degradation. In this context, the multi objective cost function for the optimisation problem considered in MPC is chosen as

$$J = \sum_{i=k}^{k+N} [J_{bat}(i) + J_{fc}(i) + J_{sc}(i) + J_{bal}(i)] \quad (5)$$

where J_{bat}, J_{fc}, J_{sc} are the cost terms pertaining to battery, FC, SC while J_{bal} pertains to cost of using dispatchable generation and imposing power curtailment in the microgrid.

1) BATTERY COST FUNCTION
The battery cost term J_{bat} is selected as

$$J_{bat}(i) = \lambda_{soc} \cdot SOC_{bat}(i)^2 \\ + \lambda_{dbat} \cdot (SOC_{bat}(i+1) - SOC_{bat}(i))^2 \quad (6)$$

where $\lambda_{soc}, \lambda_{dbat}$ are weighting factors for each term in J_{bat} and SOC_{bat} is the SOC of battery.

The cost function for the battery does not explicitly penalise the battery power, p_{bat}. As there is no explicit penalisation of p_{bat} the surplus power from PV system will be readily stored in the battery for later use. This promotes an increased utilisation of battery. In terms of operating efficiency, the increased utilisation of battery presents a better choice as the round cycle efficiency of battery is higher than 90% [41].

Nevertheless, battery degradation rate should be minimised as much as possible during the operation. This is achieved with cost function in (6). The battery degradation arises from calender and cycling ageing [42]. The former is a result of the increased dwell times at high SOC levels in the battery. Penalising SOC_{bat} in (6) will limit high SOC dwell times whenever possible and reduces calender ageing. The second term in (6) penalises the battery cycling. Excessive charge-discharge cycles have been found to accelerate cycling ageing mechanism in Li-ion battery [42]. The penalisation in (6) can limit the ageing arising from this phenomena. Though (6) appears to penalise the SOC of battery, indirectly it is the p_{bat} that is being modified to ensure minimisation of (6). The forecast based scheduling in MPC allows for better
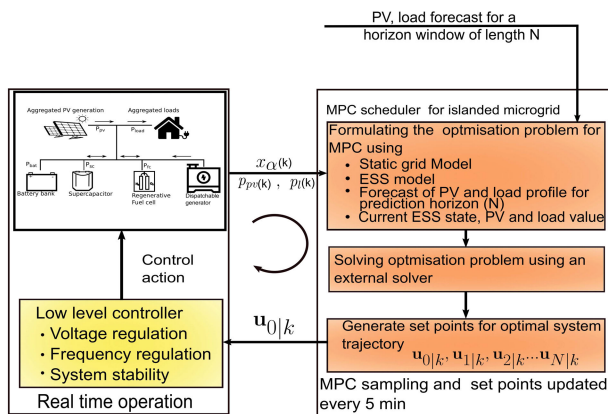

FIGURE 3. Schematic representation of the MPC scheduling process in islanded microgrid.

reduction in battery degradation, especially calender ageing. The utilisation of forecast allows MPC to have information of future generation and load profile. This facilitates altering the battery charge-discharge cycle such that the battery is not kept in a charged state for longer duration, thereby reducing the calender ageing.

It should be noted that explicit utilisation of the battery degradation equation was not considered here as it is non linear. This can result in optimisation problems that are more complex and computationally intensive [43] to solve. In order avoid this, the cost function is kept quadratic, as in (6), which will result in a quadratic programming (QP) problem that can be solved efficiently [44].

2) REGENERATIVE FUEL CELL COST FUNCTION
The fuel cell cost term J_{fc} is given by

$$J_{\text{fc}}(i) = \lambda_{\text{fc}} \cdot \frac{p_{\text{fc}}(i)^2}{p_{\text{fc}}^{max}} + \lambda_{\text{rate}} \cdot (p_{\text{fc}}(i+1) - p_{\text{fc}}(i))^2 \quad (7)$$

where $\lambda_{\text{fc}}, \lambda_{\text{rate}}$ are the weighting factors and p_{fc}^{max} is the maximum power that can be delivered by FC. The regenerative FC is characterised by poor round cycle efficiency [41]. Therefore, in order to maintain high operational efficiency the utilisation of FC should be minimised as much as possible by penalising the same, as shown in (7). Penalising the FC power by using a high value for λ_{fc} ensures that the FC utilisation happens only after the battery is either fully charged or discharged, thereby increasing operating efficiency.

Regarding the ageing mechanism of FC, a major cause is the degradation of the electrocatalyst layer under fuel starvation. The fuel starvation arises when there is a sudden change in the power set point applied to the FC system. As the FC system tries to increase the power output there is higher consumption of fuel at the electrodes. In the event of sudden increase in power output, the consumed fuel is not replenished at the same rate by the fuel delivery system, which has a slower response time. This leads to fuel starvation and irreversible damage at the electrodes [45]. The second term in (7) limits the sudden set point change thereby limiting this degradation mechanism. The availability of forecast of generation and load demand allows the MPC to control the FC profile, such that the rate of change of set points are minimised.

3) SUPERCAPACITOR COST FUNCTION
In the case of SC, the objective of the energy management system is to ensure that sufficient reserves are maintained in the SC at all instances. This allows the SC to meet the sudden imbalances arising in the grid and maintain system stability. To this extent the J_{sc} penalises the deviation of SOC_{sc} from a nominal value (SOC_{nom}). The J_{sc} is chosen as

$$J_{sc}(i) = \lambda_{\text{sc}}(SOC_{\text{sc}}(i) - SOC_{\text{nom}})^2 \quad (8)$$

where λ_{sc} is the weighting factor. The SOC_{nom} is kept at 0.5 so that there is always half the SC capacity available.

4) POWER BALANCE ENSURING COST FUNCTION
As discussed in Section II-B, the energy management stage determines the optimal value of p_{curr}. The higher curtailment of PV power leads to reduced operation of the PV array in the MPPT mode, thus reducing the PV power utilisation. Therefore, the objective of the MPC will be to minimise the p_{curr} for increasing the PV power utilisation. The same is applied to p_{gen}. The higher utilisation of dispatchable generator means more load is being catered by them and lesser utilisation of PV power. Nevertheless, these two variable are also essential to ensure the reliable grid operation according to (4). Minimising the value of $p_{\text{curr}}, p_{\text{gen}}$ can be achieved using the cost function

$$J_{\text{bal}}(i) = \lambda_{\text{gen}} \cdot \frac{p_{\text{gen}}(i)^2}{p_{\text{gen}}^{max}} + \lambda_{\text{curr}} \cdot \frac{p_{\text{curr}}(i)^2}{p_{\text{pv}}^{max}} \quad (9)$$

where $\lambda_{\text{curr}}, \lambda_{\text{gen}}$ are the weighting factors, p_{gen}^{max} is the maximum power rating of the generator and p_{pv}^{max} is the maximum power rating of the PV array. In order to ensure maximum utilisation of renewable generation the weighting factors $\lambda_{\text{curr}}, \lambda_{\text{gen}}$ are chosen to be greater than that of battery and FC cost function.

The use of forecast information in the decision making of MPC allows better utilisation of PV power through minimal curtailment and reliance on dispatchable generation. The forecast information enables the MPC to alter ESS utilisation such that ESS capacity will be available as much as possible to cater the PV power. This will be demonstrated through the results in Section IV.

C. CONSTRAINTS
The constraints address physical and electrical operating limits of ESS and associated power converters. The physical limits on the ESS are expressed through

$$x_\alpha^l \leq x_\alpha(i) \leq x_\alpha^u|_{\alpha=\{bat,sc,FC\}} \quad (10)$$

where x_α^l, x_α^u are the upper, lower bounds for ESS storage capacity. The lower bound on SOC also prevents deep discharge which can degrade the batteries. Hard constraints introduced as in (10) can result in infeasibility of solution in MPC. In order to ensure convergence, soft constraints are introduced for (10). This allows for the violation of bounds but at the cost of heavy penalisation [46]. The soft constraints are given by

$$x_\alpha^l - \epsilon_\alpha \leq x_\alpha(i) \leq x_\alpha^u + \epsilon_\alpha|_{\alpha=\{bat,sc,FC\}} \quad (11)$$

where $\epsilon_\alpha \in \mathbb{R}^3$ is the slack variable that represents the extent of violation on the original bounds (10). In order to ensure that this violation is minimal a penalisation term has to be added to the cost function in (5). This additional term is chosen as

$$J_{\text{slack}} = \rho^T \cdot \epsilon_\alpha^2 \quad (12)$$

where $\rho \in \mathbb{R}^3$ represents the penalising factor for the slack variables.

Constraints on the power delivery capability of interfacing power converters and dispatchable generator are introduced through

$$p_\alpha^{min} \leq p_\alpha(i) \leq p_\alpha^{max}|_{\alpha=\{bat,sc,fc\}}$$
$$0 \leq p_{\text{gen}}(i) \leq p_{\text{gen}}^{max} \qquad (13)$$

where p_α^{min}, p_α^{max} are the minimum, maximum power ratings of interfacing converters and p_{gen}^{max} is the rated power of the generator unit. These are maintained as hard constraints, as violation of the same can result in irreversible damage to power electronic and generator systems.

1) MLD CONSTRAINTS

The hybrid dynamical model of (2) represents a system behaviour that varies depending on the nature of the power flow in ESS (charging or discharging). Such models cannot be directly used in a conventional optimisation problem. The hybrid dynamical model needs to be converted into a mixed logical dynamic (MLD) model comprising of boolean and auxiliary variables as explained in [47]. The MLD formulation of the ESS model in (2) and constraint (13) is given by

$$x_\alpha(i+1) = x_\alpha(i) + \frac{T_s}{C_\alpha} \cdot z_\alpha(i) \cdot (\eta_\alpha - \frac{1}{\eta_\alpha})$$
$$- \frac{T_s \cdot \eta_\alpha}{C_\alpha} \cdot p_\alpha(i) \qquad (14)$$
$$-p_\alpha^{min} \cdot \delta_\alpha(i) \leq p_\alpha(i) - p_\alpha^{min}$$
$$-p_\alpha^{max} \cdot \delta_\alpha(i) \leq -p_\alpha(i)$$
$$z_\alpha(i) \leq p_\alpha^{max} \cdot \delta_\alpha(i)$$
$$z_\alpha(i) \geq p_\alpha^{min} \cdot \delta_\alpha(i)$$
$$z_\alpha(i) \leq p_\alpha(i) + p_\alpha^{max} \cdot (1 - \delta_\alpha(i))$$
$$z_\alpha(i) \geq p_\alpha(i) + p_\alpha^{min} \cdot (1 - \delta_\alpha(i))$$
$$\forall x = \{\text{SOC, LOH}\}, \alpha = \{bat, SC, fc\} \qquad (15)$$

where $\delta(i) \in \{0, 1\}$ such that $[\delta(i) = 1] \leftrightarrow [p_\alpha \geq 0]$ and $z_\alpha(i) = \delta(i) \cdot p_\alpha$. The δ_α, z_α are the boolean and auxiliary variables respectively. The boolean variable indicates whether the ESS is in a charging or discharging state (in this case $\delta_\alpha = 1$ is discharging). The auxiliary variable has been introduced to avoid the multiplicative term ($\delta_\alpha \cdot p_\alpha$) so as to avoid non-linear formulations. It was also necessary to redefine (13) to complete the MLD formulation, so that the appropriate constraint based on the charging or discharging state, of ESS, is enforced.

The use of MLD constraints in optimisation problems with quadratic cost results in a Mixed integer quadratic programming (MIQP) problem. Solvers like Gurobi [48] use algorithms like branch and bound (BB) [49], to solve these type of problems.

Representing the manipulated inputs ($[p_\alpha, p_{\text{gen}}, p_{\text{curr}}, \epsilon_\alpha]$) to the microgrid as **u**, the optimisation problem considered in

MPC is given by

$$\min_{\mathbf{u}} \left[J(\mathbf{u}, x_\alpha) \triangleq \sum_{i=k}^{k+N-1} [J_{bat}(i) + J_{fc}(i) + J_{sc}(i) \right.$$
$$\left. + J_{\text{bal}}(i) + J_{\text{slack}}(i)] \right] \qquad (16)$$

subject to

$$\textit{ESS model (14) in variable } x_\alpha$$
$$\textit{Grid model (4)}$$
$$\textit{Constraints (11), (13), (15).} \qquad (17)$$

Finally, it should be noted that MPC is formulated such that the operational efficiency is not only improved by limiting the use of regenerative FC to periods where the battery cannot cater imbalance power. The use of MLD models for ESS, accounting for their efficiencies, and use of QP in optimisation problem ensures that the energy conversion processes in microgrid are minimised. These conversions from renewable to stored energy in ESS or between different ESS always results in losses. As the MPC identifies the optimal trajectory (for converter set points) in terms of operational efficiency, the information regarding ESS efficiencies allow the MPC to ensure that unwanted conversion of energy is minimised, thus maximising operational efficiency.

D. FUZZY INFERENCE BASED ENERGY SCHEDULING

Fuzzy inference is a method of mapping input variables to output decision variables using a defined procedure that is heuristic in nature. In fuzzy inferencing the space of each input is divided into fuzzy sets [50]. Each fuzzy set will be associated with a membership function which can take a value between 0 to 1 and defines the degree of membership of an input variable to each set. The first step of the inferencing process is fuzzification of the inputs. This is the process of identifying the degree of membership of each input, based on its value, to a fuzzy set using the membership function. The next step involves fuzzy implication where fuzzy rules are used to map the fuzzified inputs to an output. Simple *if-then* rules are considered which are defined based on the designers prior knowledge of the system. The *if* part of the rule is the antecedent which are combined through *AND/OR* logical operators for the different inputs. The consequent is the *then* part of the rule which defines to which fuzzy set of the output variable the antecedent is mapped. The implication process also defines the degree of membership of the output variable to an output fuzzy set. The final step is aggregation and defuzzification. At any instant, for a given input value, multiple rules can be active resulting in outputs with varying degree of membership to multiple output fuzzy sets. In the aggregation process these outputs are aggregated and using defuzzification methods like centroid or bisector or middle of maximum, converted to a crisp output value. For a detailed exposition on fuzzy systems and inferencing process interested readers are directed to [51], [52].

Through proper selection of fuzzy sets and membership functions, fuzzy inferencing have been proved to provide a reasonable approximation of an optimal input-output mapping in the decision making problem [53], hence the same has been considered in this work. It should be noted that the capability of fuzzy inference system to ensure an approximation of the optimal input-output mapping depends extensively on prior understanding of system behaviour and resulting rule formulation from the designer. This can be difficult in complex system like electrical networks.

The input/output mapping of the fuzzy inference based energy management system is shown in Fig.4. The inputs for the energy management system are the states of the ESS, and the imbalance power, $p_{def} = p_{pv} - p_{load}$, in the grid. The outputs are set points for the p_{sc}, p_{fc} and p_{gen}. Mamdani fuzzy inference methodology [54] is employed here with 34 rules mapping the inputs to the outputs.
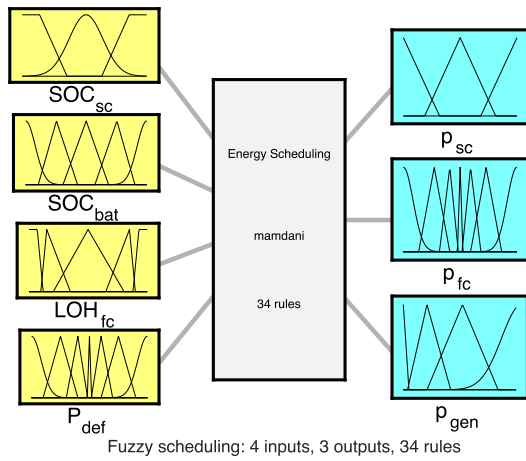

FIGURE 4. Fuzzy inference scheme for the energy management in autonomous microgrid operation.

The fuzzy sets for the input, output variables and the associated membership functions are shown in Fig. 5. The range of fuzzy sets and the membership function shapes
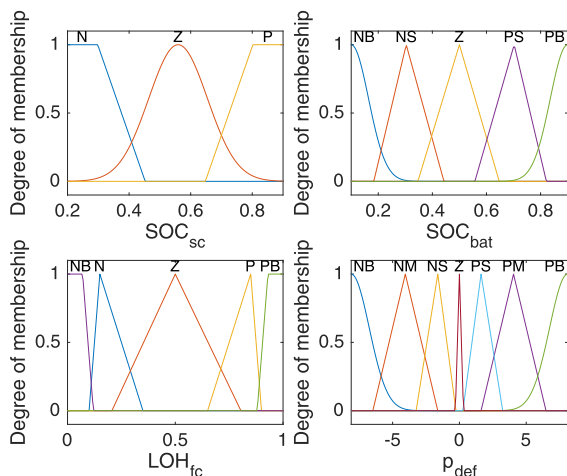

FIGURE 5. Fuzzy sets for the input variables and their membership functions.

were defined using an iterative procedure to obtain the best results. The N,Z,P define the categorizing of the associated input variable value as negative, zero and positive by the fuzzy sets. Similarly, NS, NM, NB define negative small, negative medium and negative big categorization of input value. Finally, the PS, PM, PB defines the positive small, positive medium and positive big categorization. The underlying objective in defining the rules for fuzzy based energy scheduling is to ensure maximum operational efficiency and utilisation of renewable source. In this context, the rules were defined such that any imbalance power in the grid will be catered by the battery and when the SOC_{bat} reaches its limits the regenerative FC is utilised. The SC rules were formulated such that any deviation from nominal SOC value (0.5) will result in charging or discharging just like in MPC. The Fig.6 shows outputs from fuzzy system and their dependency on relevant inputs as a surface plot. In comparison to MPC, it is difficult to address the degradation issues with fuzzy inference. This requires incorporating future generation and load values to calculate SOC_{bat} and ΔSOC_{bat}. Even if this can be achieved, incorporating them as inputs and defining explicit rules so that battery degradation is minimised is complex.
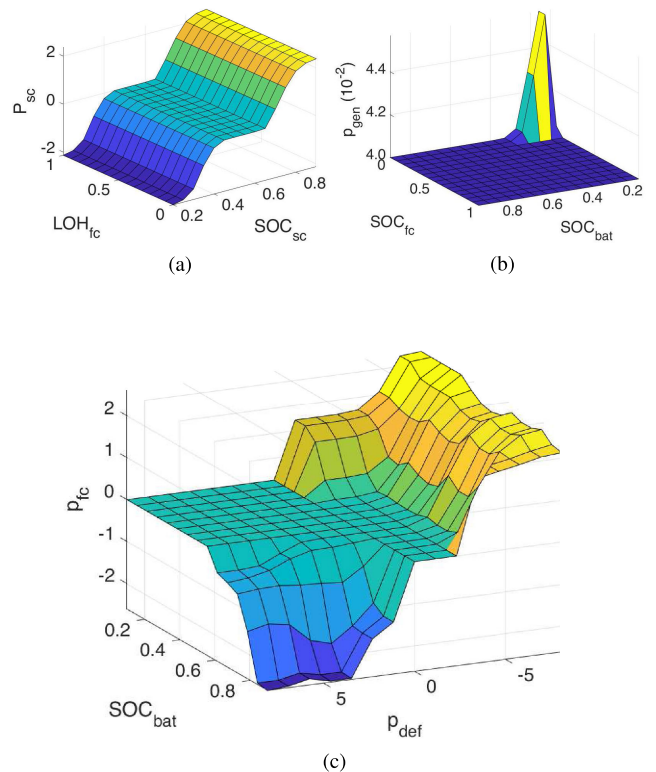

(a)   (b)

(c)

FIGURE 6. The different fuzzy inference output surfaces showing the correlation between (a) p_{sc} with LOH_{fc} and SOC_{sc}, (b) p_{gen} with LOH_{fc} and SOC_{bat} and (c) p_{fc} with SOC_{bat} and p_{def}.

In the fuzzy system it can be noticed that p_{bat} is not considered as one of the output variables. This has been left as a free variable and the value was decided outside the fuzzy system to ensure the power balance in the grid. It is

difficult to incorporate the power balance constraint inside the fuzzy system. The decision process for p_{bat} is shown in Fig.7. The decision on power curtailment and modification of dispatchable generator set points, to ensure power balance, is also made outside the fuzzy system as shown in Fig.7.
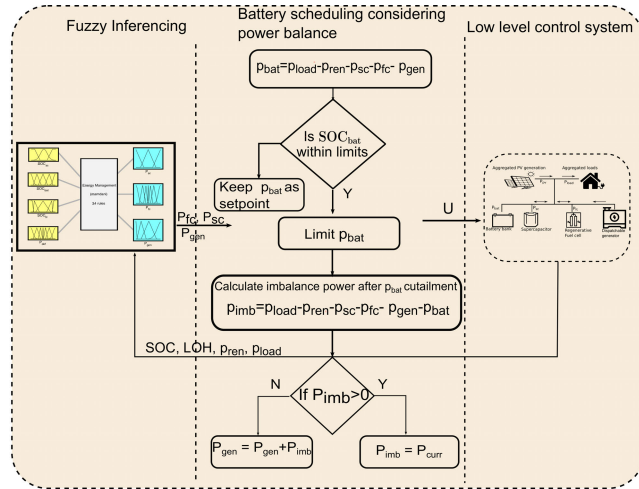

FIGURE 7. Flow chart of fuzzy inference base energy management for the autonomous microgrid operation.

IV. RESULTS

The capacities of hybrid ESS, dispatchable generating unit, the parameters and the penalisation weight values used in the MPC are listed in Table 1. The optimisation problems in MPC were solved using Gurobi (version 8) [48] with YALMIP as the parser in the MATLAB environment. The fuzzy inference scheme was realised using the Fuzzy Logic Designer tool from Matlab (version 2018b). All the algorithms were run in an Intel i7 2 core, 2.5 GHz processor and 8 GB RAM machine. The microgrid emulated in this work is based on the data obtained from a test case microgrid based in Lindenberg, Germany [37]. The sampling interval for the

TABLE 1. System parameters and their values used.

Parameter	Value
C_{sc}	0.5 kWh
C_{bat}	9 kwh
C_{FC}	32 kWh
Prediction horizon length, N	24 hours
Sampling time (T_s)	5 min
$p_{bat}^{min}, p_{bat}^{max}$	3 kW
$p_{sc}^{min}, p_{sc}^{max}$	32 kW
$p_{fc}^{max}, p_{fc}^{min}$	3kW
p_{gen}^{max}	5kW
$SOC_{bat}^l, SOC_{sc}^l, LOH_{fc}^l$	0.1
$SOC_{bat}^u, SOC_{sc}^u, LOH_{fc}^u$	0.9
SOC_{nom}	0.5
$\lambda_{SOC}, \lambda_{dbat}$	1, 10
$\lambda_{fc}, \lambda_{rate}$	10,10
$\lambda_{gen}, \lambda_{curr}$	25,25
λ_{sc}	10
ρ	100

data from Lindenberg was 5 min. As mentioned before, since the deterministic MPC is considered the forecast to the MPC, at any sampling instant, will be the actual generation and load demand for that prediction horizon.

A. ESS SIZING

Prior to discussing the results, a short discussion is provided explaining the rationale behind sizing of ESS. The problem of sizing the ESS is not the main focus of this work and as such an in depth analysis of the same will not be provided. The work in [55] provides an interesting approach for sizing grid connected batteries, considering annual PV generation and load demand. The similar approach was undertaken in this work to determine the battery capacity. If the total energy annually generated by PV system (E_{pv}) is higher than the annual energy demanded by load (E_{load}) then battery capacity is determined based on load demand

$$C_{bat} = 0.5 \cdot E_{load} \tag{18}$$

whereas if annual PV power generated (E_{pv}) is less than load demand then

$$C_{bat} = 0.5 \cdot E_{pv}. \tag{19}$$

This sizing criteria ensures that there is a trade off between economic factors and battery degradation [55]. The regenerative FC's hydrogen storage capacity was chosen such that it can cater to at least one week operation. This ensures energy sufficiency for a week's islanded operation. Typically intentional islanded operation is enforced for a short duration ranging from days to weeks, hence one week's energy sufficiency is considered for islanded operation.

B. RESULTS AND ANALYSIS OF MPC BASED ENERGY MANAGEMENT

The selection of weights, used in the optimisation problem of MPC, was done intuitively such that the utilisation of PV power is maximised. In this context, it was always ensured that λ_{gen}, λ_{curr} was kept higher than the penalising weights of ESS. Another important criteria in the weight selection was to keep λ_{soc} low. A high value for the same will force the battery to keep its SOC at a low value throughout islanded operation. This leads to under utilisation of battery and subsequent over utilisation of regenerative FC, resulting in lower operational efficiency.

The Fig.8 and Fig. 9 show one week scheduling results for the islanded microgrid with MPC and Fuzzy based energy management schemes respectively. The MPC is operated with a prediction horizon of 24 hours, considering daily periodicity of generation and load profiles. The results correspond to the second week of April. The obvious advantage of MPC, over the fuzzy scheduler, stems from the fact that the MPC utilises forecast of generation, load profile in its decision making. The effect of the same can be observed by comparing the ESS behaviour with the two scheduling techniques.

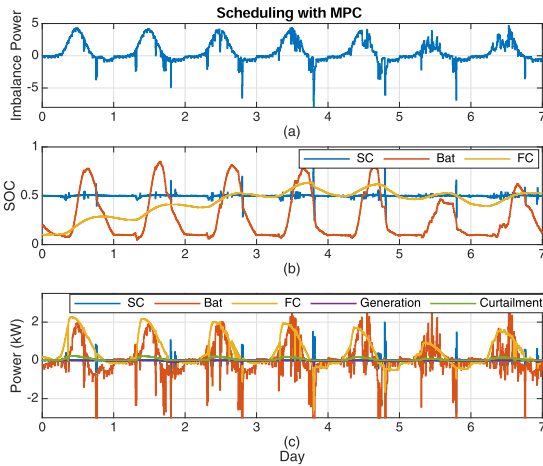This is highlighted with Fig.10, which illustrates typical daily battery power and SOC profile with MPC and Fuzzy

FIGURE 8. Scheduling results with MPC in microgrid (a) Imbalance power to be managed by the ESS and generating unit, (b) SOC evolution of the ESS, (c) Power profile of ESS, generating unit and power curtailment.
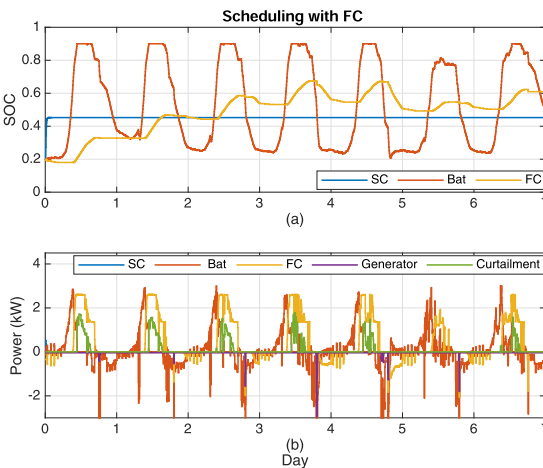

FIGURE 9. Scheduling results with fuzzy scheduler in microgrid for the same imbalance power profile as in Fig.8 (a) SOC evolution of the ESS, (b) Power profile of ESS, generating unit and power curtailment.
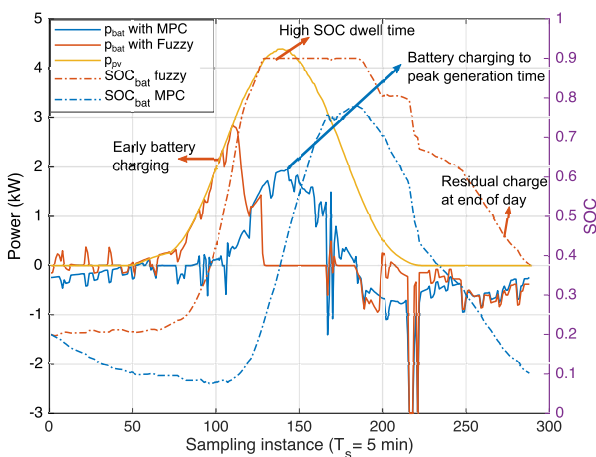

FIGURE 10. Typical daily battery power and SOC profile comparison with MPC and fuzzy based scheduler along with PV power profile for the considered day.

schemes. The profile in Fig.10 is that of the first day shown in Fig.8 and Fig. 9. The major difference between the two schemes is in temporal behaviour of the battery charging

TABLE 2. Curtailed and generated energy with different scheduling methods.

Scheduling method	Curtailment	Generation
MPC	9.27 **kWh**	1.70 **kWh**
Fuzzy scheduler	19.51 **kWh**	8.28 **kWh**

profile. As discussed before, the fuzzy scheduler rules are defined to ensure high operational efficiency. As there is no information regarding the predicted generation or load, this results in battery being charged earlier in the day whenever surplus power is available, to ensure most of the energy is handled by the battery. This is highlighted in Fig.10. The charging of the regenerative FC will happen after the full charge of the battery, as evident in Fig.9. The early charging leads to battery being kept in fully charged state for a longer time as also shown in Fig.10. This increased dwell time at high SOC is detrimental to battery as it leads to calender ageing.

In comparison, the battery charging with MPC is shifted to the period of high PV generation rather than early in the day. The availability of generation and load forecast allow the MPC to make its decision not only considering operational efficiency but also battery degradation. The shifting of battery charging to peak generation period ensures that the battery is fully charged later in the day, as seen in Fig.10. As a result, MPC facilitates a reduction in dwell time at high SOC levels and calender ageing. Another important aspect is that, since the forecast is available the MPC knows in advance the load demand for the day and the battery will be charged considering the same. This ensures that later in the day, when the battery caters the load demand the stored charge gets completely utilised leaving the battery with no residual charge at the end of the day. This again reduces the dwell time at charged level of the battery. This is also shown in Fig.10.

The lower dwell times at high SOC levels achieved with MPC is demonstrated effectively with the bar graph of Fig.11. The amount of time the battery spends in highly charged state (>0.8) is significantly higher in the case of Fuzzy based
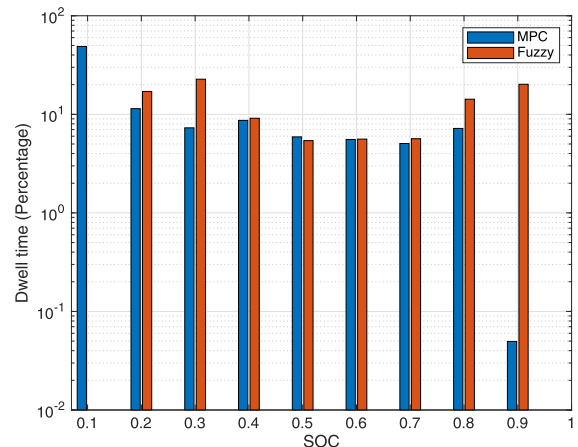

FIGURE 11. Comparison of the dwell times at different SOC levels in the battery for MPC and Fuzzy based scheme.

scheduling. This is a general issue with all heuristics based scheduling schemes, as they make the decision based on current sampled values unlike forecast based analytical methods like MPC. The dwell times at high SOC level with fuzzy scheme can accelerate the calender ageing of the battery.

In the case of regenerative FC, MPC scheduling ensures a very smooth set point (p_{fc}) variation unlike the Fuzzy scheme as shown in Fig.8 and Fig. 9. The degradation in the regenerative FC system is mainly caused by fuel starvation due to sudden changes in the FC set points. Preventing these sudden set point changes can be easily achieved with MPC scheme through cost function formulation as in (7). Incorporating the same in the Fuzzy scheduler makes the decision making process complicated as the control system designer will have to state explicitly what the optimal set point change should be in the FC. As a result, incorporating this constraint on the FC set point change is difficult in fuzzy scheduling. However, the issue of sudden set point variation can be effectively addressed in the low-level controllers using rate limiting techniques which can protect the FC by providing a gradual set point variation.

C. IMPACT OF PREDICTION HORIZON

The performance of MPC based scheduling is influenced by the choice of the prediction (control) horizon, which also affects the computational resources required. The increased need for computational resources is one of the major drawbacks with MPC over fuzzy system.

1) COMPUTATIONAL COMPLEXITY ANALYSIS

As larger prediction horizons are considered the number of variables for which the optimisation problem is to be solved increases. This results in an increase in computational time needed. Besides, the nature of the optimisation problem also affect the computational complexity. In this work the optimisation problem is of MIQP type, as MLD formulations were used for incorporating the hybrid ESS models. However, it has been well established that MIQPs are NP-complete [56]. They are usually solved with algorithms like Branch and Bound techniques [49], the computational complexity of which in the worst case scenario is the size of the entire search space [57]. In the problem considered here with binary decision variables this is $\mathcal{O}(2^{3 \cdot N})$. However, solvers like Gurobi employs a significantly efficient implementation of Branch and Bound algorithm which reduces the computation time complexity significantly. Despite this, as the length of the prediction horizon increases the algorithm tend to show a rapid increase in computation times. This is highlighted in Fig.12 where average computation times for the MPC is compared for a MIQP and QP optimisation problem, for varying lengths of prediction horizon. The QP problem was realised without considering the hybrid model of the ESS by using (1). Though the QP problem cannot capture the hybrid behaviour of ESS, this comparison allows to highlight the exponential increase in computational time
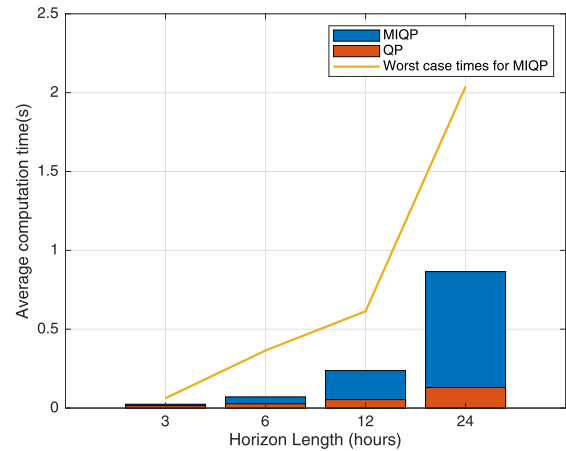

FIGURE 12. Bar graph showing average computation times for MIQP and QP problem in MPC at constant sampling time, T_s, for various control horizon lengths. The worst case computation time in the MIQP for different horizon lengths is also shown.

encountered with MIQP. The QP problems are solved in polynomial time [44].

The rapid increase in computational time with MPC (having MIQP) as the prediction horizon increases, highlight the scalability issues. In a small system, as considered here, this does not pose a major problem, as the average and the worst case computation times for solving MIQP (for all horizon lengths) is still less than the sampling interval of 5 min. However, in larger systems where more ESS are needed to be represented with hybrid models, the computation time with MIQP in MPC can reach very high values exceeding the sampling period. This can make the implementation of online scheduling with MPC, using hybrid model, impractical in such cases.

In comparison, the heuristic fuzzy inference based system requires an average computation time of 1 ms for its decision making.

2) ANALYSIS OF SCHEDULING PERFORMANCE WITH PREDICTION HORIZON

As discussed above, the larger computation times with MPC, as length of prediction horizon increases, can make them impractical for online implementation. In this problem, as mentioned earlier, the 24 hr prediction horizon was considered due to the daily periodicity of generation and load profiles. This ensures that at any instant, the MPC makes it decision considering entire load demand and generation for the day. However, if scalability is an issue in larger systems it will be beneficial to analyse the system performance when MPC is utilising shorter prediction horizons.

The Fig. 13 and Fig. 14 shows the performance of the MPC for shorter lengths of prediction horizon (3,6 and12 hours), in comparison to 24 hour length discussed before. The performance is assessed based on the battery behaviour, PV power curtailment and utilisation of the dispatchable generator unit for the same one week period discussed before.
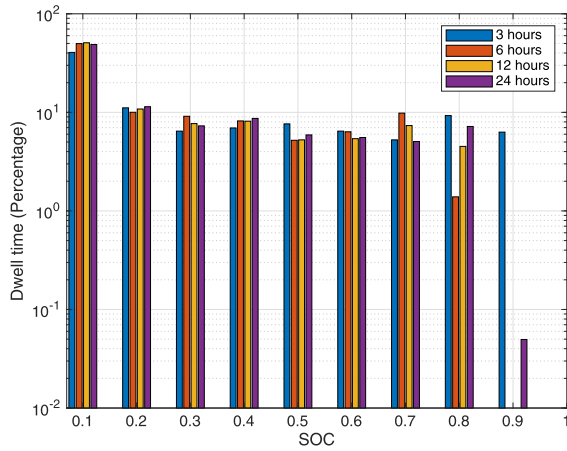
FIGURE 13. Comparison of dwell times at various SOC levels for different lengths of prediction horizon with MPC.
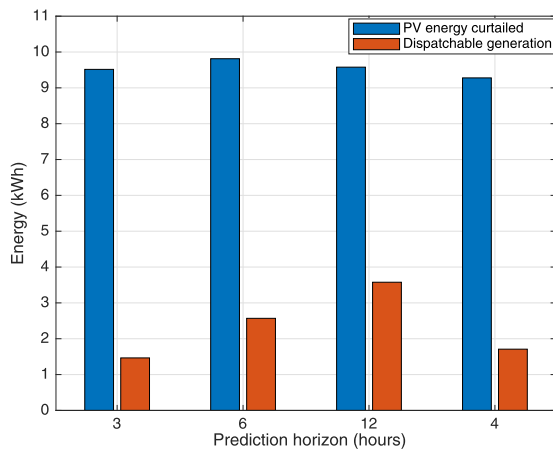

FIGURE 14. Comparison of PV power curtailment and energy from dispatchable generating units for different lengths of prediction horizon with MPC.

As the prediction horizon is shortened the MPC will have to make the scheduling decisions without having the full information of the generation profile. This can lead to early battery charging and increased dwell times at high SOC levels, as in Fuzzy scheduling. This is ascertained through the results demonstrated in Fig.13, where the battery dwell time at various SOC levels are compared when using MPC with different prediction horizon lengths. In the case of 3 hour prediction horizon the dwell time of the battery at high SOC levels (>0.8) is comparable to the fuzzy scheme as shown in Fig.11.

In the case of 6 and 12 hour prediction horizon the MPC has more information regarding the generation profile. This allows the shifting of battery charging to peak generation period and lowering dwell times at high SOC level, as shown in Fig.13. It should be noted that with the 24 hour prediction horizon the battery is kept at a highly charged state (0.9) for more time than in the case of 6 and 12 hours. This is because, when the prediction horizon is reduced the entire information of load demand is not available to MPC. As a

result, the battery is charged without accounting for total load demand. In some cases this can lead to battery not storing sufficient charge for the meeting entire load demand. In the 24 hour prediction window this is not the case and the battery will store higher charge to cater the total load demand, leading to increased dwell time at higher SOC levels. This is also clear from Fig.14, where the 6 and 12 hour prediction window cases has to rely more on the dispatchable generating unit to cater the load demand in comparison to the 24 hour case.

In terms of PV power curtailment and utilisation of dispatchable generator, the performance with shorter prediction horizons were similar to that of the 24 hour case. In all the cases (3, 6, 12 hours) the PV curtailment with MPC was lesser than that of the fuzzy scheduler system.

This concludes that in shorter prediction horizons of 6 and 12 hours, the MPC performance is similar to the 24 hour case without undergoing significant deterioration in system performance, while also reducing computational complexity. In comparison to the fuzzy scheme, the MPC with shorter horizon still ensures an improved performance. As a result, if computational complexity associated with larger systems is a concern, MPC can be employed with shorter prediction horizons.

V. CONCLUSION

An MPC based energy scheduling system was developed for an autonomous islanded microgrid with PV, dispatchable generator and hybrid ESS. The MPC based energy scheduling exhibited improved performance over a fuzzy based heuristic scheme due to its ability to make decisions accounting for the future generation and load demand. The improvements with MPC are summarised as

- Significant reduction in dwell time at high SOC levels of battery (>0.8) by shifting battery charging to peak generation period.
- Smoother set-point variation in regenerative FC using MPC.
- Almost 50% and 80% reduction in PV power curtailment and dispatchable generator use with MPC. This highlights increased utilisation of PV power.

In terms of computational requirement, MPC was more demanding in comparison to the fuzzy scheme. Nevertheless for the islanded microgrid considered in this work, the worst case computational time encountered with the 24 hour prediction window was significantly lower than the 5 minute sampling interval used.

Finally, as future work the research should be extended to asses the performance of MPC when there is uncertainty in forecast. An important step in this direction will be to develop uncertainty models, that better describe the real world scenario, which can be used in simulation studies. Stochastic MPC techniques should also be considered in future research as means of optimal decision making under forecast uncertainty.

REFERENCES

[1] S. Papathanassiou, N. Hatziargyriou, P. Anagnostopoulos, L. Aleixo, B. Buchholz, C. Carter-Brown, N. Drossos, B. Enayati, M. Fan, V. Gabrion, B.-N. Ha, L. Karstenti, J. Malý, W. Namgung, J. Pecas-Lopes, J. R. Pillai, T. Solvan, and S. Verma, "Capacity of distribution feeders for hosting der," CIGRÉ Working Group C6.24, 2014.

[2] D. Maxwell. *Parts of Northern Ireland's Electricity Grid Overloaded*. BBC. Accessed: Nov. 3, 2013. [Online]. Available: https://www.bbc.com/news/uk-northern-ireland-24921411

[3] M. S. Whittingham, "History, evolution, and future status of energy storage," *Proc. IEEE*, vol. 100, no. Special Centennial Issue, pp. 1518–1534, May 2012.

[4] M. G. Molina, "Energy storage and power electronics technologies: A strong combination to empower the transformation to the smart grid," *Proc. IEEE*, vol. 105, no. 11, pp. 2191–2219, Nov. 2017.

[5] E. Schaltz, A. Khaligh, and P. O. Rasmussen, "Influence of battery/ultracapacitor energy-storage sizing on battery lifetime in a fuel cell hybrid electric vehicle," *IEEE Trans. Veh. Technol.*, vol. 58, no. 8, pp. 3882–3891, Oct. 2009.

[6] A. Khaligh and Z. Li, "Battery, ultracapacitor, fuel cell, and hybrid energy storage systems for electric, hybrid electric, fuel cell, and plug-in hybrid electric vehicles: State of the art," *IEEE Trans. Veh. Technol.*, vol. 59, no. 6, pp. 2806–2814, Jul. 2010.

[7] P. Denholm, E. Ela, B. Kirby, and M. Milligan, "Role of energy storage with renewable electricity generation," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-6A2-47187, 2010.

[8] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, and Y. Ding, "Progress in electrical energy storage system: A critical review," *Prog. Natural Sci.*, vol. 19, no. 3, pp. 291–312, Mar. 2009.

[9] T. Ackermann, G. Andersson, and L. Söder, "Distributed generation: A definition," *Electr. Power Syst. Res.*, vol. 57, no. 3, pp. 195–204, Apr. 2001.

[10] J. A. P. Lopes, C. L. Moreira, and A. G. Madureira, "Defining control strategies for microgrids islanded operation," *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 916–924, May 2006.

[11] T. Basso, "IEEE 1547 and 2030 standards for distributed energy resources interconnection and interoperability with the electricity grid," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-5D00-63157, 2014.

[12] J. M. Guerrero, J. C. Vasquez, J. Matas, L. García de Vicuna, and M. Castilla, "Hierarchical control of droop-controlled AC and DC microgrids—A general approach toward standardization," *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 158–172, Jan. 2011.

[13] D. E. Olivares, A. Mehrizi-Sani, A. H. Etemadi, C. A. Cañizares, R. Iravani, M. Kazerani, A. H. Hajimiragha, O. Gomis-Bellmunt, M. Saeedifard, R. Palma-Behnke, G. A. Jiménez-Estévez, and N. D. Hatziargyriou, "Trends in microgrid control," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1905–1919, Jul. 2014.

[14] A. Bidram and A. Davoudi, "Hierarchical structure of microgrids control system," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1963–1976, Dec. 2012.

[15] H. Kanchev, D. Lu, F. Colas, V. Lazarov, and B. Francois, "Energy management and operational planning of a microgrid with a PV-based active generator for smart grid applications," *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4583–4592, Oct. 2011.

[16] P. Garcia, L. M. Fernandez, C. A. Garcia, and F. Jurado, "Energy management system of Fuel-Cell-Battery hybrid tramway," *IEEE Trans. Ind. Electron.*, vol. 57, no. 12, pp. 4013–4023, Dec. 2010.

[17] M. Kisacikoglu, M. Uzunoglu, and M. Alam, "Load sharing using fuzzy logic control in a fuel cell/ultracapacitor hybrid vehicle," *Int. J. Hydrogen Energy*, vol. 34, no. 3, pp. 1497–1507, Feb. 2009.

[18] D. Gayme and U. Topcu, "Optimal power flow with large-scale storage integration," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 709–717, May 2013.

[19] T. A. Nguyen and M. L. Crow, "Stochastic optimization of renewable-based microgrid operation incorporating battery operating cost," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 2289–2296, May 2016.

[20] R. Dufo-López, J. L. Bernal-Agustín, and J. Contreras, "Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage," *Renew. Energy*, vol. 32, no. 7, pp. 1102–1126, Jun. 2007.

[21] F. Garcia-Torres, L. Valverde, and C. Bordons, "Optimal load sharing of hydrogen-based microgrids with hybrid storage using model-predictive control," *IEEE Trans. Ind. Electron.*, vol. 63, no. 8, pp. 4919–4928, Aug. 2016.

[22] M. Khalid and A. V. Savkin, "A model predictive control approach to the problem of wind power smoothing with controlled battery storage," *Renew. Energy*, vol. 35, no. 7, pp. 1520–1526, Jul. 2010.

[23] A. Parisio, E. Rikos, and L. Glielmo, "A model predictive control approach to microgrid operation optimization," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 5, pp. 1813–1827, Sep. 2014.

[24] E. Mayhorn, K. Kalsi, M. Elizondo, W. Zhang, S. Lu, N. Samaan, and K. Butler-Purry, "Optimal control of distributed energy resources using model predictive control," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2012, pp. 1–8.

[25] J. Ramos-Teodoro, F. Rodríguez, M. Berenguel, and J. L. Torres, "Heterogeneous resource management in energy hubs with self-consumption: Contributions and application example," *Appl. Energy*, vol. 229, pp. 537–550, Nov. 2018.

[26] M. Trifkovic, M. Sheikhzadeh, K. Nigim, and P. Daoutidis, "Modeling and control of a renewable hybrid energy system with hydrogen storage," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 1, pp. 169–179, Jan. 2014.

[27] A. Cecilia, J. Carroquino, V. Roda, R. Costa-Castelló, and F. Barreras, "Optimal energy management in a standalone microgrid, with photo-voltaic generation, short-term storage, and hydrogen production," *Energies*, vol. 13, no. 6, p. 1454, Mar. 2020.

[28] Y. Du, J. Wu, S. Li, C. Long, and S. Onori, "Coordinated energy dispatch of autonomous microgrids with distributed MPC optimization," *IEEE Trans. Ind. Informat.*, vol. 15, no. 9, pp. 5289–5298, Sep. 2019.

[29] X. Xing, L. Xie, and H. Meng, "Cooperative energy management optimization based on distributed MPC in grid-connected microgrids community," *Int. J. Electr. Power Energy Syst.*, vol. 107, pp. 186–199, May 2019.

[30] S. Zhou, Z. Hu, W. Gu, M. Jiang, and X.-P. Zhang, "Artificial intelligence based smart energy community management: A reinforcement learning approach," *CSEE J. Power Energy Syst.*, vol. 5, no. 1, pp. 1–10, 2019.

[31] V.-H. Bui, A. Hussain, and H.-M. Kim, "Q-Learning-Based operation strategy for community battery energy storage system (CBESS) in microgrid system," *Energies*, vol. 12, no. 9, p. 1789, May 2019.

[32] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement learning: A survey," *J. Artif. Intell. Res.*, vol. 4, no. 1, pp. 237–285, Jan. 1996.

[33] E. Ela, M. Milligan, and B. Kirby, "Operating reserves and variable generation," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-5500-51978, 2011.

[34] B. Zakeri and S. Syri, "Electrical energy storage systems: A comparative life cycle cost analysis," *Renew. Sustain. Energy Rev.*, vol. 42, pp. 569–596, Feb. 2015.

[35] T. Esram and P. L. Chapman, "Comparison of photovoltaic array maximum power point tracking techniques," *IEEE Trans. Energy Convers.*, vol. 22, no. 2, pp. 439–449, Jun. 2007.

[36] Y. Yang, F. Blaabjerg, and H. Wang, "Constant power generation of photovoltaic systems considering the distributed grid capacity," in *Proc. IEEE Appl. Power Electron. Conf. Expo. (APEC)*, Mar. 2014, pp. 379–385.

[37] M. Bost, B. Hirschl, and A. Aretz, *Effekte Von Eigenverbrauch und Netzparität bei der Photovoltaik*. Berlin, Germany: Institut für ökologische Wirtschaftsforschung (IÖW) GmbH, gemeinnützig, 2011.

[38] J. B. Rawlings and D. Q. Mayne, *Model Predictive Control: Theory and Design*. Madison, Wisconsin: Nob Hill Pub., 2009.

[39] M. Arnold, R. R. Negenborn, G. Andersson, and B. De Schutter, "Model-based predictive control applied to multi-carrier energy systems," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2009, pp. 1–8.

[40] F. Adamek, M. Arnold, and G. Andersson, "On decisive storage parameters for minimizing energy supply costs in multicarrier energy systems," *IEEE Trans. Sustain. Energy*, vol. 5, no. 1, pp. 102–109, Jan. 2014.

[41] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, and Y. Ding, "Progress in electrical energy storage system: A critical review," *Prog. Natural Sci.*, vol. 19, no. 3, pp. 291–312, Mar. 2009.

[42] J. Vetter, P. Novák, M. R. Wagner, C. Veit, K.-C. Möller, J. O. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, and A. Hammouche, "Ageing mechanisms in lithium-ion batteries," *J. Power Sources*, vol. 147, nos. 1–2, pp. 269–281, 2005.

[43] J. W. Chinneck. (2006). Practical optimization: A gentle introduction. Syst. Comput. Eng., Carleton Univ., Ottawa, ON, Canada. [Online]. Available: http://www.sce.carleton.ca/faculty/chinneck/po.html

[44] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[45] A. Taniguchi, T. Akita, K. Yasuda, and Y. Miyazaki, "Analysis of electrocatalyst degradation in PEMFC caused by cell reversal during fuel starvation," *J. Power Sources*, vol. 130, nos. 1–2, pp. 42–49, May 2004.

[46] E. C. Kerrigan and J. M. Maciejowski, "Soft constraints and exact penalty functions in model predictive control," in *Proc. UKACC Int. Conf. (Control)*, 2000.

[47] A. Bemporad and M. Morari, "Control of systems integrating logic, dynamics, and constraints," *Automatica*, vol. 35, no. 3, pp. 407–427, Mar. 1999.

[48] *Gurobi Optimizer Reference Manual*, Gurobi Optimization. Inc., Beaverton, OR, USA, 2015.

[49] P. M. Narendra and K. Fukunaga, "A branch and bound algorithm for feature subset selection," *IEEE Trans. Comput.*, vol. C-26, no. 9, pp. 917–922, Sep. 1977.

[50] A. Rosenfeld, "Fuzzy groups," *J. Math. Anal. Appl.*, vol. 35, no. 3, pp. 512–517, Sep. 1971.

[51] C. C. Lee, "Fuzzy logic in control systems: Fuzzy logic controller. II," *IEEE Trans. Syst., Man, Cybern.*, vol. 20, no. 2, pp. 419–435, Mar./Apr. 1990.

[52] C. H. Chen, *Fuzzy Logic and Neural Network Handbook*. New York, NY, USA: McGraw-Hill, 1996.

[53] B. Kosko, "Fuzzy systems as universal approximators," *IEEE Trans. Comput.*, vol. 43, no. 11, pp. 1329–1333, Nov. 1994.

[54] E. H. Mamdani and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," *Int. J. Man-Machine Stud.*, vol. 7, no. 1, pp. 1–13, Jan. 1975.

[55] J. Moshövel, K.-P. Kairies, D. Magnor, M. Leuthold, M. Bost, S. Gährs, E. Szczechowicz, M. Cramer, and D. U. Sauer, "Analysis of the maximal possible grid relief from PV-peak-power impacts by using storage systems for increased self-consumption," *Appl. Energy*, vol. 137, pp. 567–575, Jan. 2015.

[56] A. D. Pia, S. S. Dey, and M. Molinaro, "Mixed-integer quadratic programming is in NP," *Math. Program.*, vol. 162, nos. 1–2, pp. 225–240, Mar. 2017.

[57] W. Zhang, "Branch-and-bound search algorithms and their computational complexity," Inf. Sci. Inst., Univ. Southern California, Marina Del Rey, CA, USA, Tech. Rep. ISI/RR-96-443, 1996.

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