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Research paper

Artificial intelligence-enabled probabilistic load demand scheduling with dynamic pricing involving renewable resource

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ABSTRACT

Residential demand response is one of the key enabling technologies which plays an important role in managing the load demand of prosumers. However, the load scheduling problem becomes quite challenging due to the involvement of dynamic parameters and renewable energy resources. This work has proposed a bi-level load scheduling mechanism with dynamic electricity pricing integrated with renewable energy and storage system to overcome this problem. The first level involves the formulation of load scheduling and optimization problems as optimal stopping problems with the objective of energy consumption and delay cost minimization. This problem involved the real-time electricity pricing signal, customers load scheduling priority, machine learning (ML) based forecasted load demand, and renewable & storage unit profiles, which is solved using mathematical programming with branch-and-cut & branch-and-bound algorithms. Since the first-level optimization problem is formulated as a stopping problem, the optimal time slots are obtained using a one-step lookahead rule to schedule the load with the ability to handle the uncertainties. The second level is used to further model the load scheduling problem through the dynamic electricity pricing signal. The cost minimization objective function is then solved using the genetic algorithm (GA), where the input parameters are obtained from the first-level optimization solution. Furthermore, the impact of load prioritization in terms of time factor and electricity price is also modeled to allow the end-users to control their load. Analytical and simulation results are conducted using solar-home electricity data, Ausgrid, AUS to validate the proposed model. Results show that the proposed model can handle uncertainties involved in the load scheduling process along with a cost-effective solution in terms of cost and discomfort reduction. Furthermore, the bi-level process ensures cost minimization with end-user satisfaction regarding the dynamic electricity price signal.

1. Introduction

With the rapid industrial growth and large-scale penetration of electric vehicles (Chen et al., 2020; Pan et al., 2020), the global energy demand has been drastically increased (Zeng et al., 2018; Ahmad and Zhang, 2020). Besides most of the demand capacity is fulfilled through fossil-fuel-based generation sources (Nguyen et al., 2018; IEA, 2021a). Consequently, the increased use of thermal power sources is the main contributor to the increase in CO_2 emissions (Konda et al., 2018; Erdinç et al., 2017), which is one of the major causes of global warming. In contrast, adopting the other meaningful ways to manage the increasing load demand along with the reduction in greenhouse gas emissions is still a challenging problem that must be solved on a global scale to promote energy sustainability (Hoffman, 2022). In the recent past, while reducing the supply–demand gap through the combination of thermal, nuclear, and other energy resources (Wei et al., 2019; Baniasadi et al., 2019; Moazeni et al., 2021; Gabbar and Abdussami, 2019; Tao et al., 2018; Zhou et al., 2016; Abdussami and Gabbar, 2019), the consideration of power generation through renewable energy (IEA, 2020) and hydrogen sources (IEA, 2021b; Yusaf et al., 2022) has been promoted to significantly reduce greenhouse gas emissions (Algarni et al., 2021; Cheng et al., 2020; Wang et al., 2020). Because renewable and hydrogen energy resources are becoming widely adopted as new and alternative sources of energy to supply power to both residential and commercial sectors.

On the other hand, over the past few years, the power grid has been overburdened due to a steady increase in peak load demand

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Nomenclature

Indices

$i \in I$	Index of load
$s \in S$	Index of state
$t \in T$	Index of time

Binary Variables

α	Binary decision variable
η_{st}	On/off state of storage system
ν_{st}	Startup state of storage system
ψ_{st}^{in}	Initial state of storage system
$a = 0$	Markov Process stop action
$a = 1$	Markov Process start action
a_i	Load arrival request
$P_{x,y}$	Probability of close set
u_{st}	Shutdown state of storage system

Other Parameters & Variables

$\acute{\lambda}_i^d(t)$	Dynamic price signal for a renewable integrated system ($/kWh)
$\acute{\Phi}ed(t)$	Energy consumption cost based on dynamic price of renewable integrated system over t ($/kWh)
β	Normalization factor
$\mathbb{E}_t$	Expected cost ($/kWh)
γ	Dynamic threshold
$\lambda(t)$	Electricity unit price over t ($/kWh)
$\lambda^{max}(t)$	Max. electricity unit price over t ($/kWh)
$\lambda^{min}(t)$	Min. electricity unit price over t ($/kWh)
$\lambda_i^d(t)$	Electricity price difference
$\mathbb{N}$	Natural number
μ_i	Probability of ith user/load
$\overline{\acute{\Phi}ed(t)}$	Upper limit on cost with renewable integrated dynamic price ($/kWh)
$\overline{\Phi\xi(t)}$	Max. social welfare cost over t ($/kWh)
$\overline{\psi_{dt}^-}$	Upper limit on storage discharging (kW)
$\overline{\psi_{st}^+}$	Upper limit on storage charging (kW)
$\overline{e_{re}(t)}$	Upper limit on renewable energy
$\Phi ed(t)$	Energy consumption cost over t ($/kWh)
$\Phi(t)$	Total cost over t ($/kWh)
$\Phi\xi(t)$	Social welfare cost over t ($/kWh)
ψ_{dt}^-	Storage unit discharging capacity
ψ_{st}	Renewable energy storage capacity
ψ_{st}	Storage capacity (kW)
ψ_{st}	Surplus energy (kW)
ψ_{st}^+	Charging capacity of storage unit
$\psi_{st}(t-1)$	Storage capacity during $t-1$
τ	Time duration of a slot
τ_0	Time slot at 0 time instant
$\tau_{i,f}$	Finishing time of ith user
$\tau_{i,r}$	Required duty cycle of ith load
$\tau_{i,s}$	Starting time of ith user
$\tilde{\Phi}ed(t)$	Energy consumption cost based on dynamic price over t ($/kWh)
$\underline{\acute{\Phi}ed(t)}$	Lower limit on energy consumption cost based on dynamic price of renewable integrated system over t ($/kWh)
$\underline{\psi_{dt}^-}$	Lower limit on storage discharging (kW)
$\underline{\psi_{st}^+}$	Lower limit on storage charging (kW)
$\underline{e_{re}(t)}$	Lower limit on renewable energy
φ_{ct}	Discharging state
φ_{dt}	Discharging state
ϱ_{st}	Storage power loss (kW)
e_g	Grid energy source (kW)
e_{re}	Renewable energy source (kW)
e_{st}	Storage energy source (kW)
$ed_i(t)$	Load demand over time t (kW/h)

and is more fragile due to the integration of electric vehicles (Yao et al., 2017; Qian et al., 2011). Such type of situation may pose a profound threat to the power grid and create a great challenge to energy retailers in constructing realistic electricity prices (Chen and Chang, 2018; Markovic et al., 0000; Gao et al., 0000; Tanriöven et al., 0000; Ma et al., 2020; Mansor et al., 2019). Thus, in the presence of distributed energy resources and variable energy demand trends, it seems difficult to manage the demand with the consideration of exogenous and endogenous variables. Moreover, in the presence of dynamic energy consumption trends and the intermittent nature of renewable energy sources due to weather and habitual conditions, constant measures are inevitable to be taken to maintain a balance between the energy demand and supply. Consequently, the optimization and control strategies without considering dynamic variables and the active participation of consumers seem ineffective. Therefore, the present work focuses on energy demand management with the integration of variable energy resources (VERs), active consumers, and time-varying electricity pricing without heavily relying on grid energy. The next section provides an overview of the motivation behind this work along with its real contribution.

2. Relevant literature

The load scheduling & optimization topic has been well studied by different authors (Panda et al., 2022; Chowdhury et al., 2018; Beaudin and Zareipour, 2015; Panda et al., 2021a; Premkumar et al., 2022; Panda et al., 2021b; Behera and Jain, 2021; Chen et al., 2019; Ahmadzadeh et al., 2021; Wen et al., 2022; Hassan et al., 2022; Tehrani et al., 2022; Kelepouris et al., 2022). Furthermore, demand-side load scheduling & management (Panda et al., 2022; Beaudin and Zareipour, 2015; Panda et al., 2021a; Premkumar et al., 2022; Panda et al., 2021b; Behera and Jain, 2021; Chen et al., 2019; Tehrani et al., 2022) and dynamic price-based optimization algorithms (Wen et al., 2022; Hassan et al., 2022; Mohandes et al., 2021; Al-Rubaye et al., 2018; Ferdous et al., 2020; Lu et al., 2021; Yang et al., 0000; Almahmoud et al., 0000; Hung and Michailidis, 0000; Lu and Hong, 2019; Mishra and Parida, 0000; Zhou et al., 0000) are well explained in different comprehensive surveys. Generally, these load scheduling algorithms are developed based on price-based demand response strategies (Huang et al., 0000; Wang et al., 0000b; Rasheed et al., 2016) with the objectives of electricity cost minimization (Zeng et al., 2018), peak-reduction (Nguyen et al., 2018; Golmohamadi et al., 2019), and social-welfare maximization (Rasheed et al., 2019; Asgher et al., 2018). Wen et al. (2022) have proposed a dynamic price-based demand response program to minimize the cost and discomfort of end-users. The dynamic time warping clustering method has been used to differentiate customers who are willing to participate in load management programs offered by utility service providers. Then game-theoretic approach is used to establish equilibrium among service providers and customers to maximize their profits. Hassan et al. (2022) have proposed a Demand Response enhancing Differential Pricing (DRDP) algorithm to devise a dynamic pricing strategy along with smart meter data privacy. To improve user comfort, Tehrani et al. (2022) have presented a dynamic electricity pricing algorithm for residential load equipped with the energy storage system. This algorithm works in both normal and emergency conditions, where the outage patterns are modeled in different hours to provide the end-users with uninterruptible power supply. The demand response users that caused high and/or rebound peaks are only charged high prices. Mohandes et al. (2021) have proposed a compensation scheme for load balancing within the defined time horizon. Where a bi-interval-based piece-wise reward function is devised to provide financial incentives to the customers. To further maximize the reward and social welfare of customers, the small contracts have been designed & optimized, accordingly. Finally, a MILP objective function is formulated and solved using the decomposition technique. Al-Rubaye et al. (2018), has proposed a new pricing mechanism considering real-time pricing (RTP) and load demand. This work has significantly managed the electricity prices for users having a balanced load curve. However, the customers with balanced load demand profiles are provided with the pricing tariff under aggregated load demand. Perhaps, it is relatively difficult for market retailers to provide a separate tariff to each customer. Otherwise, it may pose a communication overhead as massive data exchange could have occurred between the users and utility. Another load scheduling scheme based on dynamic pricing is devised to manage the trading-off between the utility and user regarding profit maximization (Ferdous et al., 2020). The work reported by Lu et al. (2021) has used a reinforcement learning algorithm for a decision support system based on an individual user to devise an optimal electricity pricing plan for end-users. Markov decision theory is used to formulate optimization problems without considering transition probability. This decision support system selects the best optimal pricing plans based on the energy demand requirement of any user to minimize the cost and dissatisfaction through different incentives and rewards. Furthermore, the Q-learning algorithm is also used to handle the possible uncertainties for improved performance and results. Although this work has provided significant results regarding user satisfaction, however, user satisfaction could be affected if the energy demand varies after the selection of an optimal pricing plan. Yang et al. (0000) have used a density-based spatial clustering algorithm to devise energy consumption patterns of customers based on the historical dataset. Then, these load profiles & price levels are used to devise the retail prices to minimize the energy consumption cost. The work of Almahmoud et al. (0000) is devoted to matching supply–demand ratio & peak load management through threshold-based pricing policy under a dynamic environment. Initially, the price thresholds are assigned in different time intervals to minimize the peak load demand. Then, electricity prices are constructed to match supply–demand capacity. Another load management mechanism with a dynamic pricing model is proposed to devise customized prices considering load demand variations (Hung and Michailidis, 0000). As these variations are being observed by the randomized load patterns, therefore, the Monte Carlo algorithm has been used to flatten the load patterns. In contrast, the excessive use of traditional energy generation facilities may also raise climate concerns. Therefore, to handle these types of problems, a load control mechanism to manage the energy resources without relying on thermal energy generation facilities is required. For this purpose, the researchers have already proposed an autonomous load scheduling mechanism (Lu and Hong, 2019). Huang et al. (0000) have scheduled the multi-energy load integrated with photovoltaic and storage systems. Then a scenario-based stochastic non-convex mixed integer nonlinear programming-based objective function has been formulated to minimize the operational cost of the production facility. Wang et al. (0000b), have proposed an integrated demand response mechanism to minimize the operational cost of the energy system. Where an interval method has been adopted to overcome the uncertainty of integrated demand response programs. Results reveal that this approach is effective in saving costs when compared to counterpart methods. Although, this approach has produced satisfactory results in terms of cost reduction, however, a lack of uncertainty analysis mechanism has made it infeasible in realistic scenarios.

Rezaei et al. (2022) have proposed a demand side integration based dynamic pricing mechanism for demand side load management with the objective of profit maximization of utility. Where the end-users agreed in participating load management programs are offered dynamic prices to facilitate them in terms of cost reduction. The optimization problem is formulated as a stochastic optimization problem with mixed integer nonlinear programming that involved a probabilistic representation of uncertain generation and renewable energy resources. To cope with the challenge of multi-residential demand response, Nguyen et al. (2022) have proposed a holistic bidirectional demand-side management approach for excess power sharing and improved performance. Kumar et al. (2021) have proposed a stochastic energy management framework to analyze the flexible load management strategy and price & incentive-based pricing programs. The main objective is to ensure end-users affordability & reliability in the presence of non-dispatchable energy resources. Ding et al. (0000) have developed a real-time locational marginal pricing scheme to identify the equilibrium points. Then, load demand has been modeled as a linear function that is monotonously decreasing. However, it seems difficult to solve this function in the presence of primary and/or dual variables. Therefore, the primal problem has been further decomposed into a convex quadratic sub-problem through duality theory. However, it is worth mentioning here that without modeling inherent uncertainties and other control variables involved in finding the equilibrium points, the expected results may deviate. It allows electricity operators to purchase electric power following their defined producers to further design the electricity tariffs based on the demand–supply theory of economics. Here, the users do not allow to maximize their profit and/or comfort. However, the homogeneous & non-homogeneous users are still required to be priced based on load demand despite the pricing policy obtained from advanced forecasting algorithms. The work demonstrated by Konda et al. (2018) has integrated the PV and wind energy resources to fulfill the demand capacity with reduced CO2 emissions. Furthermore, it is shown by Rana et al. (2018) that load demand can also be managed through the integration of renewable energy and electrification transportation. However, regarding autonomous energy management, the SG technology is being adopted to provide the opportunity to energy retailers, prosumers, and market participants to manage the demand capacity through the consideration of price-based mechanisms and customer engagement. However, to best manage the load demand, there is a need to engage the residential customers in active load management programs.

2.1. Motivation and contributions

Energy generation and management through active participation of prosumers are the ongoing challenges being faced by today's power sector. This is due to the ever-increasing world population and the rapid advancements in information and communication technology (Outlook, 2014). In contrast, the capability of distributed generating and transmission of power is increasing at a much slower pace. This is due to the limits on power generating units including hydro-power and thermal. Whereas, thermal power generation is not very popular due to carbon dioxide emissions (Annual Energy Outlook, 2021) and high oil prices in the World. Therefore, the development of a load management mechanism (Al-jabery et al., 2017) with efficient utilization of VERs is necessary for the ongoing collective prosperity and quality of life (Park et al., 0000). This has to lead to the consideration of activities or programs to promote the reduction in energy consumption or/and management through active participation. The former considers efficient building materials (Laustsen, 2008) and smart loads (NEC, 2021), while the latter focused on the development of efficient load scheduling and optimization techniques. The demand response technologies (Wang et al., 0000a,c; Nguyen et al., 2020; Chen et al., 2013) bring the need for a dynamic framework for addressing the financial settlement in the electricity market, where the temporal components are necessary due to the intermittent nature of renewable energy sources due to weather conditions and EVs due to dynamic user behaviors. The real-time electricity price (Mishra and Parida, 0000; Zhou et al., 0000) can be viewed as a state of this dynamic framework. This is because it determines financial transactions of control variables and various market entities, that can affect consumption. Thus, interrelation among market clearing pricing, pricing mechanisms, and demand are grouped under the rubric of dynamic control necessitating optimization-based solutions. The optimization-based autonomous load scheduling and energy management mechanism is needed to cope with one or more of the below-mentioned challenges. The energy management systems confront some practical difficulties due to uncertainties regarding renewable energy resources (Athari and Wang, 2016; Nazemi et al., 0000; Ben Rached et al., 2017) and charging behaviors of EVs in residential and parking lots. Since the existing load scheduling schemes (Rana et al., 2018; Chen et al., 2020) are based on residential demand response with the integration of VER and storage systems, particularity is not highly suitable (Yao et al., 2017; Qian et al., 2011; Chen and Chang, 2018; Markovic et al., 0000; Gao et al., 0000; Tanriöven et al., 0000; Ma et al., 2020; Mansor et al., 2019). This is due to real-time changes in market-clearing prices, user satisfaction due to these variations, algorithmic scheduling errors due to dynamic variations in power generation and consumption trends, and the impact of the integration of VER and storage units (Wei et al., 2016; Muhanji et al., 2018), capacity scheduling, and optimizing the energy reserve units, particularly. Therefore, to handle the aforementioned uncertainties and limitations regarding the load scheduling perspective, this work adopts a slightly different approach to load management considering the underlying uncertainties (i.e., electricity pricing, user behavior, demand variation, uncertainties in renewable and storage capacity). The main contributions are:

1. A bi-level load scheduling and optimization mechanism with the objective of energy consumption and scheduling delay cost minimization integrated with renewable energy and storage systems.
2. Mathematical models for renewable energy, storage system, electricity price & cost, scheduling delay and stopping criteria are developed to better analyze the impact of exogenous and endogenous variables on the scheduling process. Furthermore, advanced machine learning algorithms (i.e., Artificial Neural Network (ANN), Nearest Neighbors (NN), Gaussian process) are used to predict the real-time load profiles to obtain accurate scheduling results.
3. The first-level optimization objective function is formulated based on OSLR following the predefined dynamic stopping criteria to find the optimal time slots to schedule the loads with reduced cost and delay. Where the renewable energy and storage units act as first-choice during the scheduling process to further minimize the rebound peaks. Furthermore, the electricity price signal is modeled as a random process instead of the day-ahead real-time pricing (DA-RTP) signal. The first-level objective function is then solved using mathematical programming with branch-and-cut & branch-and-bound algorithms and a CPLEX solver.
4. The load scheduling problem is further modeled to introduce the dynamic electricity price signal. Then the bi-objective cost function is modeled as a stochastic optimization problem since the RTP, load demand and scheduling process are highly dynamic. Therefore, the heuristic-based GA is used to solve the objective function to ensure the minimization of cost and delay with the global optimum solution.
5. Furthermore, unlike (Yi et al., 2011), to prioritize the customers, different priorities are introduced and incorporated into the optimization program in such a way that the users have the opportunity to modify their priorities based on the load demand requirements.

3. Modeling methodology

By keeping in mind the aforementioned challenges and open research issues identified based on the literature review, this work investigates the potential of OSR based on an opportunistic algorithm (Clarke and Reed, 1990; Jacka et al., 2007; Iwayemi et al., 2011; Yi et al., 2011) and introduces a novel mechanism for load management modeling. This work is modeled in four steps: (i) in the first step, the scheduling probabilities for all loads are obtained, which later on are used to find the optimal scheduling patterns, (ii) the photovoltaic (PV) based renewable energy and storage models are designed with stochastic control parameters, (iii) energy demand consumption and scheduling delay parameters are modeled and cost minimization objective function is formulated, and (iv) the dynamic pricing signal based on the first step scheduling is obtained to distribute the cost among all users. Since the dynamic pricing signal is obtained based on the load, and optimal stopping price, therefore, each user obtained the cost based on load and scheduling patterns without directly relying on the price signal that is obtained from the retailer. Regarding implementation, different optimization algorithms are first investigated to select the best appropriate. Then, based on the relevant literature about optimization and control, this work has used linear programming (LP) for a cost minimization problem, and extended mathematical programming (EMP), and mixed-integer programming (MIP) algorithms are used to solve the cost and social welfare objective function(s), respectively.

4. Problem formulation

The proposed system model is designed to schedule the load under uncertain parameters and variable energy resources. Where the model contains renewable, storage, load, price, and delay models. The load demand $ed_i(t)$ data is obtained from Aus-Grid (Solar, 2022), while the electricity price signal λ is assumed as an independent and identically distributed process that is uniformly distributed over $t \in T$. Where, the time duration of ith load is denoted by τ_i. Let $ed_i(t)$ of ith user such that $i \in I$ over time t can be fulfilled through grid $e_g(t)$, renewable $e_{re}(t)$ and storage $e_{st}(t)$ resources, respectively. Where, the surplus energy $\left\{ed(t) - (e_g(t) + e_{re}(t) + e_{st}(t))\right\}$ can be directly integrated in the load management system or stored in backup system. Furthermore, the e_{st} is subject to the upper and lower limits during charging and discharging. Let α be the binary decision variable used to denote ON/OFF states of connected loads and $a_i(t)$ denotes the arrival requests of ith over time t. We further assume that each load starts working at the beginning of each time slot $\tau_{i,s}$ and finishes its working/duty-cycle $\tau_{i,f}$ within one or more time slots depending on the energy demand and the duty cycle requirements. However, the time taken by any process to complete the load demand requirements does not exceed the total time $\tau_{i,s} - \tau_{i,f} \leq T$. The next subsections provide the details of renewable, storage, load, price, and delay models, respectively.

4.1. Renewable energy & storage model

This work considers renewable and/or storage components as random variables whose values are not known in advance. It means, that the control unit does not know the exact available amount, and thus has to manage the demand by finding the stopping policies, which are discussed in the next sections. Furthermore, the algorithm considers renewable and storage systems as the first choice to model the load demand. Where the surplus energy is then stored in the backup storage system to use in later hours when the demand and electricity price are relatively higher. Let $e_{re}(t)$ denote the net amount of renewable energy which can be obtained from the solar photo-voltaic source over the time t. Unlike realistic renewable energy generation pattern, this work assumes a non-zero energy at any time t; $e_{re}(t) > 0$. To better analyze the impact of the proposed load scheduling mechanism, real-time prediction algorithms are used to predict $e_{re}(t)$ over the 24 h time interval.

$$e_{re} = \sum_{t=1}^{T} \{e_{re}(t)\}, \forall t \tag{1}$$

$$\underline{e_{re}(t)} \leq e_{re}(t) \leq \overline{e_{re}(t)} \tag{2}$$

Eq. (1) shows the predicted solar power is within the minimum and maximum limits. Where, $\overline{e_{re}(t)}$ and $\underline{e_{re}(t)}$ represent upper and lower limits on renewable energy capacity. Eq. (2) denotes lower and upper limits on the renewable energy capacity. Similarly, the energy storage model is considered as an infinite capacity and is used as a primary source of energy during the scheduling process. Let $ed_i(t)$ denotes the energy demand of i loads over time t, that must be fulfilled through renewable $e_{re}(t)$, storage $e_{st}(t)$ and grid energy $e_g(t)$ sources, respectively. The surplus energy $\psi_{st}(t)$ can be either used and stored in the storage units written as Eq. (3):

$$\psi_{st}(t) = \sum_{t=1}^{T} \left\{ed(t) - \left(e_g(t) + e_{re}(t) + e_{st}(t)\right)\right\}, \forall t \tag{3}$$

The energy storage system $\psi_{st}(t)$ is subject to the following limits:

$$\varphi_{ct}\underline{\psi_{st}^{+}}(t) \leq \psi_{st}^{+}(t) \leq \varphi_{ct}\overline{\psi_{st}^{+}}(t), \forall t \tag{4}$$

$$\varphi_{dt}\underline{\psi_{dt}^{-}}(t) \leq \psi_{dt}^{-}(t) \leq \varphi_{dt}(t)\overline{\psi_{dt}^{-}}(t), \forall t \tag{5}$$

$$\eta_{st}(t) = (\nu_{st}(t) - u_{st}(t)) + \eta_{st}(t-1), \forall t. \tag{6}$$

$$\psi_{st}^{in}(t) = 0 \ \ \forall t. \tag{7}$$

where, ν, u, η, ψ and φ denote startup, shutdown, on/off, initial and charging states of energy storage systems. Charging and discharging capacities during charging state $\varphi_{ct}(t)$ of the energy storage system is denoted by ψ_{st}^{+} & discharging ψ_{dt}^{-}. Where, Eq. (4) denotes the minimum and maximum limits on the energy storage system during the charging state. Similarly, Eq. (5) denotes the minimum and maximum limits on the energy storage system during the discharging state. Variables $\overline{\psi_{st}^{+}}$ & $\overline{\psi_{dt}^{-}}$ and $\underline{\psi_{st}^{+}}$ & $\underline{\psi_{dt}^{-}}$ denote upper and lower limits on charging & discharging capacity, respectively. Eqs. (6) and (7) denote switching states and initial state $\psi_{st}^{in}(t)$ of the energy storage system.

$$\underline{\psi_{st}}(t) \leq \psi_{st}^{+}(t) \leq \overline{\psi_{st}}(t) \tag{8}$$

$$\underline{\psi_{st}}(t) \leq \psi_{st}^{-}(t) \leq \overline{\psi_{st}}(t) \tag{9}$$

Eqs. (8) and (9) denote lower and upper limits on storage capacity. Here, the lower capacity is assumed zero when system starts operating, while the storage capacity is kept infinite. In other words, the zero means the lower capacity of the energy storage system must be non-negative ($\psi_{st}(t) \geq 0$), while the upper/maximum capacity of the storage system is considered infinite during implementation. However, it is also understood that the maximum storage capacity could be equal to the maximum of renewable energy capacity. Furthermore, the upper limit does not fulfill as the remaining surplus energy can only be stored.

$$\psi_{st}(t) = \psi_{st}(t-1) + \varrho_{st}(t)(\psi_{st}^{-}(t) + \psi_{st}^{+}(t)) \tag{10}$$

$$\varphi = \begin{cases} \text{if:}\varphi_{ct}(t) = 0 \ \psi_{st}^{+}(t) = 0, & \& \ \varphi_{dt}(t) = 0 \ \psi_{st}^{-}(t) = 0 \\ \text{if:}\varphi_{ct}(t) = 1 \ \psi_{st}^{+}(t) = 1, & \& \ \varphi_{dt}(t) = 1 \ \psi_{st}^{-}(t) = 1 \end{cases} \tag{11}$$

The energy storage state equation considering the loss factor $\varrho_{st}(t)$ is represented as Eq. (10). However, the proposed storage system is assumed ideal with no loss during the charging or discharging. Eq. (11) denotes the charging and discharging states, respectively.

4.2. Load & cost model

The energy $ed(t)$ demand fulfilled through grid, renewable and storage sources can be written as Eq. (12):

$$ed(t) = \sum_{t=1}^{T} \left(e_g(t) + e_{re}(t) + e_{st}(t)\right), \tag{12}$$

Energy $ed_i(t)$ consumed by all the loads i when the load demand request $a_i(t)$ arrived in time t is represented as Eq. (13).

$$ed_i(t) = \sum_{t=1}^{T}\sum_{i=1}^{I} \{ed_i(t) \times \alpha_i(t) \times a_i(t)\}, \forall i, t \tag{13}$$

where, $\alpha_i(t)$ is a binary variable [0, 1] of ith load during t that decides whether the optimal stopping criteria are fulfilled or not, and $a_{i,s}(t)$ denotes arrival time of load when stopping time exists. Let $\Phi(t)$ be the total energy consumption cost of i over t, which is equal to the sum of two types of costs as written Eq. (14):

$$\Phi(t) = \Phi ed(t) + \Phi\xi(t), \forall t \tag{14}$$

In Eq. (14), $\Phi ed(t)$ denotes the energy consumption cost, while $\Phi\xi(t)$ denotes the social welfare/scheduling delay cost. The energy consumption cost of i load is denoted as Eq. (15):

$$\Phi ed(t) = \sum_{t=1}^{T}\sum_{i=1}^{I} \{ed_i(t) \times \lambda(t)\}, \forall i, t \tag{15}$$

where, $\lambda(t)$ denotes electricity price signal obtained from a day-ahead electricity market. The energy consumption cost $\Phi ed_i(t)$ excluding renewable and storage system is calculated as Eq. (16).

$$\Phi ed(t) = \sum_{t=1}^{T}\sum_{i=1}^{I}\{(ed_i(t) - e_{re}(t) + e_{st}(t)) \times \lambda(t)\}, \forall i, t \tag{16}$$

Since, Eq. (16) is used to calculate electricity cost based on real-time electricity pricing signal $\lambda(t)$. However, customer satisfaction is generally related to the benefits in terms of bill reduction, load scheduling flexibility, or an uninterruptible supply of energy. To achieve this objective, this work has integrated the dynamic electricity pricing (Rasheed and R-Moreno, 2022) into OSR algorithm to provide the customers with demand-aware electricity prices.

4.3. Scheduling delay model

This work has modeled the scheduling delay based on customer priority, load demand requirements, electricity price information, and other uncertainties related to the algorithm. The $\Phi\xi_i(t)$ can be zero if the optimal stopping time for all loads remains the same as defined by users. Otherwise, its value will be greater than zero and less than $\overline{\Phi\xi_i(t)}$. Let $\Phi\xi_i(t)$ depend on the electricity cost at stopping time and is therefore modeled to analyze the scheduling behavior of the proposed mechanism. However, before calculating $\Phi\xi_i(t)$, the scheduling delay factor ξ_i is introduced Eq. (17).

$$\xi_i(t) = \left\{\mu_i(t) \times \tau_i(t) \times \left(\frac{a_i(t) - \tau_i}{T - \tau_{i,r}}\right)\right\}, \forall i, t \tag{17}$$

where, μ_i denotes the probability of ith load, τ_i denotes the time duration required by ith load, $\tau_{i,s}$ denotes the scheduled duty cycle and $\tau_{i,r}$ elucidates the required duty cycle, respectively. Eq. (18) calculates the scheduling delay of each load that is not serviced. The cost associated with Eq. (17) is denoted as:

$$\Phi\xi_i(t) = \{(ed_i(t) \times \lambda(t)) \times \xi_i(t)\}, \forall i, t \tag{18}$$

where, Eq. (18) shows the delay cost of ith load that is unable to meet the stopping criteria in $T-1$. If the cost $\Phi\xi_i(t)$ at t is less than the cost at state $t-1$, then the social welfare cost will be reduced and vice versa. Furthermore, $\Phi\xi_i(t)$ and $\tau_{i,r}$ are bounded by maximum time limit t and working cycle requirements are expressed though (19) and (20), respectively.

$$0 \le T - \tau_{i,r} \le T, \forall i, t \tag{19}$$

$$\tau_0 \le \tau_{i,f} \le T - 1 \tag{20}$$

4.4. Dynamic price & cost model

In the first module, the cost and delay minimization objective function is solved using MIP. Then the obtained results are used as input to the second optimization module where the GA is used to find the nondiscriminatory electricity price signals for each user. For this purpose, the scheduled load demand and optimal stopping price of each user are required to calculate the dynamic price. To calculate a dynamic electricity price signal for each user, it is first required to calculate the electricity price difference of each user based on load consumption variation. In this way, the new electricity cost based on the dynamic price signal is calculated using Eq. (15) and is expressed as Eq. (21):

$$\tilde{\Phi} ed(t) = \sum_{t=1}^{T}\sum_{i=1}^{I}\left\{ed_i(t) \times \lambda_i^d(t)\right\}, \forall i, t \tag{21}$$

where, Eq. (21) denotes energy consumption cost based on dynamic price signal, $\lambda_i^d(t)$ denotes the dynamic electricity price signal, which is calculated based on load demand, scheduling capacity, and market price variation as Eq. (22);

$$\lambda_i^d(t) = \sum_{t=1}^{T}\sum_{i=1}^{I}\left\{\frac{1}{ed_i^2(t)}(ed_i(t) \times \lambda(t))\right\}, \tag{22}$$

where, Eq. (22) denotes the different (min/max) in electricity price of each user i based on load consumption in comparison with other users. In other words, it is unlike $\lambda(t)$ which is calculated based on an aggregated load demand. Here, the initial price and load consumption profiles of each user i are obtained from the OSR implementation (optimal stopping price based on λ) using the one-step lookahead rule (OSLR) discussed next. Similarly, the cost based on renewable energy integration can also be calculated. However, it is first required to calculate the dynamic price signal $\acute{\lambda}_i^d(t)$ for a renewable integrated system using Eq. (22).

$$\acute{\lambda}^d(t) = \sum_{t=1}^{T}\sum_{i=1}^{I}\left\{\frac{1}{ed_i^2(t)}[ed_i(t) - (e_{re}(t) + e_{st}(t)) \times \lambda(t)]\right\}, \tag{23}$$

Now, the cost associated with Eq. (23) is calculated as Eq. (24):

$$\acute{\Phi} ed(t) = \sum_{t=1}^{T}\sum_{i=1}^{I}\left\{(ed_i(t) - e_{re}(t) + e_{st}(t)) \times \acute{\lambda}_i^d(t)\right\}, \forall i, t \tag{24}$$

$$\underline{\acute{\Phi} ed_i(t)} \le \acute{\Phi} ed_i(t) \le \overline{\acute{\Phi} ed_i(t)}, \forall i, t \tag{25}$$

$$0 \le \Phi\acute{\xi}_i(t) \le \overline{\Phi\acute{\xi}_i(t)}, \forall i, t \tag{26}$$

$$\underline{\acute{\Phi} ed_i(t)} > 0, \forall i, t \tag{27}$$

where, Eq. (24) is used to calculate the energy consumption cost based on optimal stopping price & $\acute{\lambda}_i^d(t)$ and load consumption patterns i, Eqs. (25) & (26) denote lower and upper limits on the energy consumption and social welfare cost and Eq. (27) shows the cost remains non-zero if $E_{d_i}(t) \ge 0$ during operation time T.

$$\Phi(t) = \sum_{t=1}^{T}\sum_{i=1}^{I}\left\{(ed_i(t) - e_{re}(t) + e_{st}(t)) + \left(\xi_i(t) \times \lambda_i^d(t)\right)\right\}, \quad \forall i, t, s \tag{28}$$

The total cost is calculated in Eq. (28) that can be obtained by adding energy consumption cost Eq. (24) and delay cost Eq. (18).

4.5. OSR working

Since OSR is a Markov Decision Process (MDP) that involved two actions; a = 0 means stop and a = 1 means continue. Therefore, two types of costs based on stopping criteria are involved Eq. (29).

$$\Phi(t) = \begin{cases}\tilde{\Phi} ed(t), & \text{if } a = 0, (stopping), Eq. (21)\\ \Phi(t), & \text{if } a = 1, (continuation), Eq. (28)\end{cases} \tag{29}$$

Fig. 1 explains the OSR process in finding the optimal time slots based on given μ, a, γ and λ, respectively. It is clear that upon service arrival request $a_i(t)$, the process stops ($a = 0$) Eq. (32) only when the optimal time slots are obtained based on γ, Eqs. (16), (29). In contrast, ($a = 1$) means the arrival request does not fulfill the stopping criteria γ and is therefore unable to provide the scheduling pattern. The arrival request(s) will remain in the waiting queue until the next feasible time slot. The process continues until the next feasible time slot is found when the stopping criteria are fulfilled. In this case, the control unit calculates the waiting time and the tariff of the time slots when the process

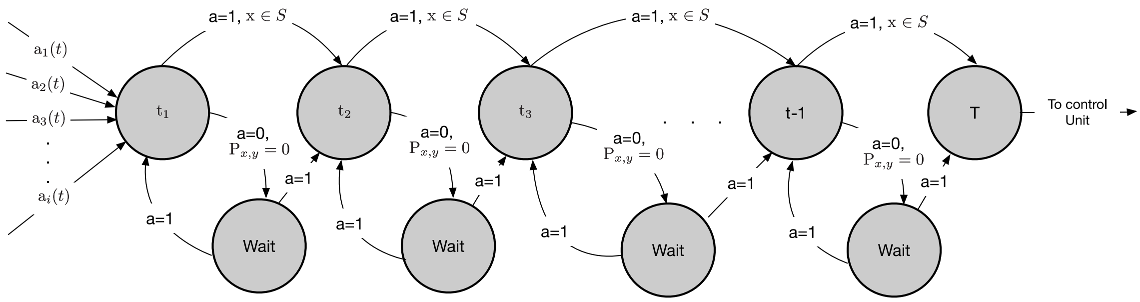


Fig. 1. Activity diagram of OSR algorithm in finding stopping time slots.

stops. Furthermore to balance power supply and demand, the proposed algorithm keeps checking the remaining time duration and the required duty cycles. Otherwise, the obtained solution would be infeasible. The OSR-based scheduling process can be further explained through the Bellman rules. Let the time be finite, then the cost in terms of the Bellman equation is expressed as:

$$\Phi(t) = \left\{min : (ed(t) - e_{re}(t) + e_{st}(t)) \times \lambda^{d}, \Phi(t) + \mathbb{E}_t\left(\Phi_{s-1}(t)(\mathbf{X})\right)\right\}, \forall t \tag{30}$$

where, Eq. (30) refers to the instantaneous cost, and $\Phi(t-1)$ is the cost during $t-1$ such that $t \in \mathbb{N}$, if the process continues. However, there is no cost involved if the process stops at the current state s. For example, if $min : \Phi_i(t)$ is found, then $\Phi_i(t_0) = \left\{ed_i(t) - e_{re}(t) + e_{st}(t) \times \lambda_i^d\right\}$ means the process has to stop if entered to the stopping state $s \in S$.

Definition 1. In one step lookahead rule (OSLR), the process stops if the state $s \in S$. Where S can be defined as:

$$S = \left\{t : (ed(t) - e_{re}(t) + e_{st}(t)) \times \lambda^{d} \le \Phi(t) + \mathbb{E}_t\Phi_{s-1}(t)(\mathbf{X})\right\}, \forall t, s \tag{31}$$

Eq. (31) refers to the set of stopping states $s \in S$, where the process stops if the optimal cost $\Phi_{i,s}(t) \le \Phi^{r}_{i,s}(t)$ is found. Otherwise, the process will continue to find the next possible state(s) with reduced cost.

Definition 2. Let assume if the stopping set is closed $S \in \mathcal{X}$, and the optimal solution is found within the closed set, the process will stop without moving to the next states. It is expressed as:

$$P_{x,y} = 0, \forall s \in S, y \notin S. \tag{32}$$

Eq. (32) shows the probability of moving to the next possible state is zero once the state y is entered in set S. Otherwise, the process continues to find the next states with optimal solution. Then for the given closed set S, OSLR states:

$$\Phi_{(s-1)}(t) = \left\{(ed(t) - e_{re}(t) + e_{st}(t)) \times \lambda^{d}(t)\right\}, \forall s, t \tag{33}$$

Furthermore, the cost $\Phi_{(s)}(t)$ at s must remains same as Eq. (33). Similarly, based on Eq. (33), if $s \in S$ is closed then $\mathbf{X} \in S$, and the cost $\Phi_{(s-1)(\mathbf{X})}(t)$ will also be equal to Eq. (34):

$$\begin{aligned}\Phi_s(t) = \Big\{&(ed(t) - e_{re}(t) + e_{st}(t)) \times \lambda^{d}(t), \Phi(t)\\ &+\mathbb{E}_t\left((ed(t) - e_{re}(t) + e_{st}(t)) \times \lambda^{d}(t), \Phi(t)(\mathbf{X})\right)\Big\}, \forall t, s\end{aligned} \tag{34}$$

4.5.1. Stopping criteria

Since the proposed cost minimization optimization problem is a finite time-stopping problem, therefore the set of states $s \in S$ given by the OSLR is generally closed and called an "optimal policy". However, if the solution is found just after $s = 1$, the OSLR is exactly an optimal stopping policy for one step only. In contrast, if the solution is not found exactly after $s = 1$, then it is better to continue for $s - 1$. Furthermore, while the λ is an independent and identically distributed process that is uniformly distributed over t. Therefore, the optimal stopping time t is that when the minimum $\lambda(t) \le \gamma(t)$:

$$\gamma_i(t) = \sqrt{\beta\left(\frac{1}{ed_i(t)}(\lambda^{max} - \lambda^{min}) \times \mu_i \times \tau_i\right)}, \forall t, s \tag{35}$$

Eq. (35) reveals that this policy is based on a pure threshold, which means that if $\lambda_i(t) \le \gamma_i(t)$, then this time is known as the stopping time. Otherwise, the process continues until the stopping time is found. Eq. (35) gives the stopping threshold when the electricity price is less than $\gamma_i(t)$. The variable $\beta = 2$ is used to normalize the Eq. (35). However, the value of β can be adjusted based on the decision requirements. Moreover, the high value of β may pose an extra delay in the decision process due to more difference between threshold and cost values. If an optimal time is not found and the process continues to the next time slots, the ξ_i would be added to the energy consumption cost. Finally, the cost minimization objective function is written as Eq. (36):

$$min \sum_{t=1}^{T}\sum_{i=1}^{I}\Phi_i(t), \tag{36}$$

subject to: Eqs. (17), (19), (20), (22), (23), (26), (25), (27), (35).

Based (36), the power allocation pattern for each load i over time t are first obtained. However, if any load is postponed due to higher electricity price λ and probability μ, the extra costs can be added. Therefore, to reduce the $\Phi(t)$, the proposed algorithm continually checks the duty cycle τ_i of each load i to meet the load demand without violating duty cycles τ_r requirements. Furthermore, if μ_i contains higher values and $min : \Phi(t)$ is not obtained due to higher λ. Then the algorithm allocates the remaining load with feasible time before the completion time τ_f.

5. Proposed algorithms

This work has used different tools to achieve the desired objectives as shown in Fig. 2. Firstly, MATHEMATICA is used to obtain the real-time predictions and the results are provided to MATLAB and GAMS. Where the GAMS is good in handling large-scale mathematical optimization and industrial problems with the ability to provide results with significant accuracy and conference rate. Secondly, the OSR is used to find the optimal time slots to schedule the load demand with the objective of cost and discomfort reduction. The main objective of considering the OSR theory (Clarke and Reed, 1990; Jacka et al., 2007) is due to the problem of choosing an optimal time to make a decision or action based on random variables to minimize an expected cost

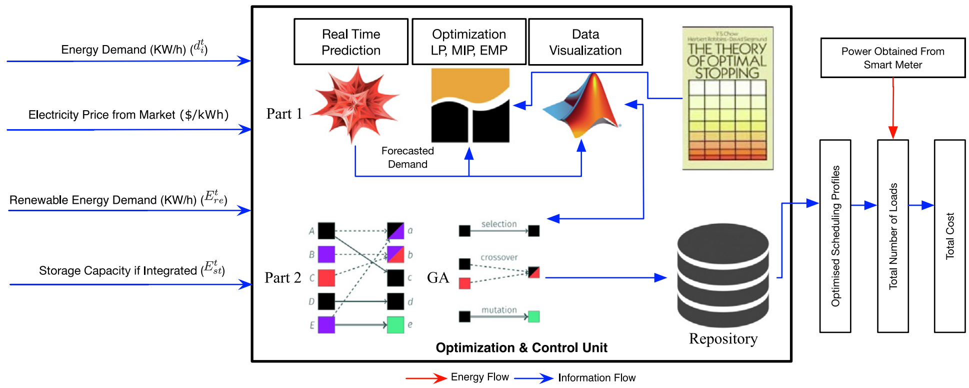


Fig. 2. Conceptual diagram of the proposed system model.

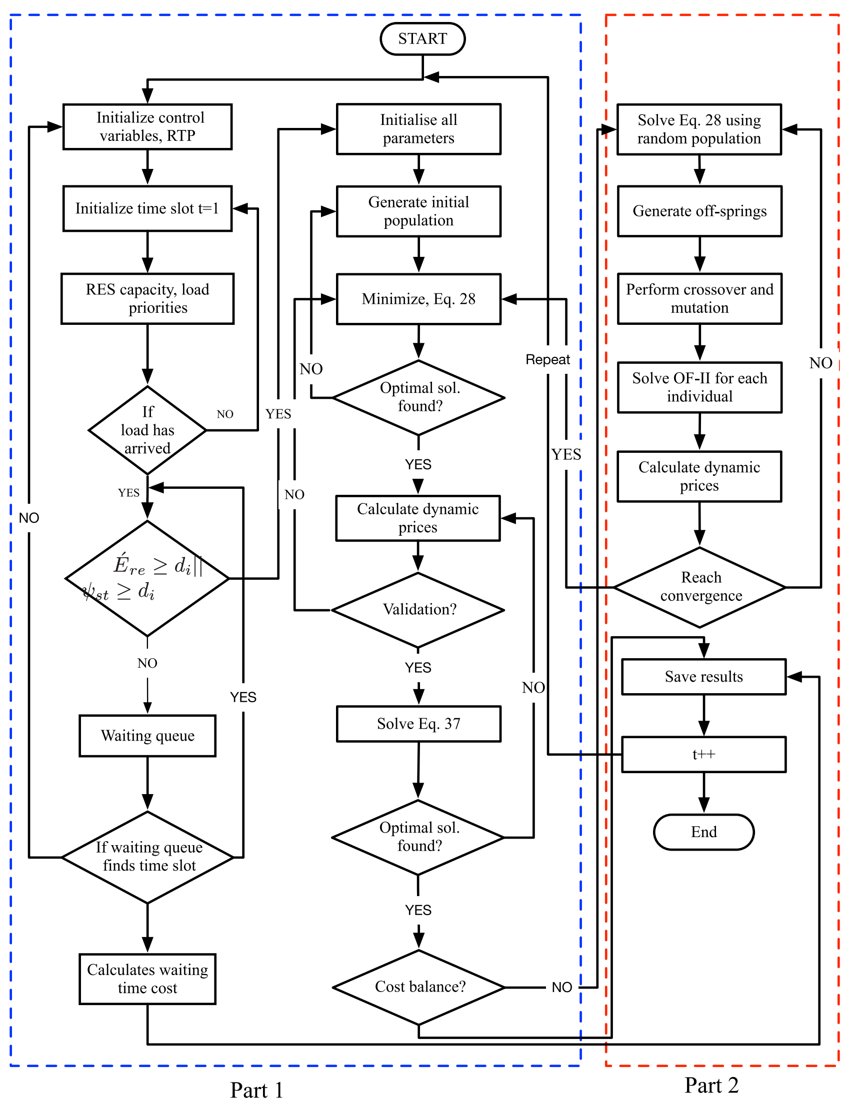


Fig. 3. Flowchart of the proposed bi-level load scheduling algorithm, (Part 1/level 1) OSR is used to schedule the load by finding the optimal time slots, and (Part 2/level 2) GA is used to further find and distribute the dynamic pricing to the consumers.

Algorithm 1 OSR Based Scheduling Algorithm.

1: Initialize t=0.
2: Initialize the scheduling cycle of loads.
3: Update current status of load over time t.
4: If load is placed in ready queue, the EMC checks $e_{re}(t)$ and $\psi_{st}(t)$.
5: If $e_{re}(t) \geq ed_i(t) \mid\mid \psi_{st}(t) \geq ed_i(t)$; turn *ON* load *i*.
6: If $e_{re}(t) < ed_i(t) \mid\mid \psi_{st}(t) < ed_i(t)$; then find $\gamma(t)$ (Eq. (35)) for load *i*.
7: If $ed_i(t) < (eg_{(}t) + e_{re}(t) + e_{st}(t))$; turn on load *i*.
8: If $ed_i(t) \geq (eg_{(}t) + e_{re}(t) + e_{st}(t))$; keep the load in waiting queue until the problem Eq. (36) is solved.
9: if min. of Eq. (36) found, save the results. Otherwise, move to step-4.
10: if $e_{re}(t) > ed_i(t) + \psi_{st}(t)$; save surplus energy.
11: t= n+1, move back to step 2 for n=24.
12: ***Remarks***: The algorithm describes the complete steps of the proposed load management and scheduling phenomenon. Before sharing the optimal time slots with loads, all loads must have prior probabilities, demand profiles, and intended time slots. Then based on this information, the scheduling algorithm finds the optimal time slots and allocates the power to all the loads placed in the ready queue. The loads can be placed in a waiting queue if the demand exceeds a certain predefined threshold. Then the combined, load consumption and scheduling are calculated using Eq. (36). It is also worth noting here that the scheduling delay is modeled to show customers the waiting time. However, when this particular load can get the scheduling horizon, the electricity unit price will remain the same during the given time frame. Unlike previous works (Gao et al., 0000; Iwayemi et al., 2011; Yi et al., 2011; Chen et al., 2020), there is no scheduling cost associated with any load except the delay profiles and electricity unit price at that particular time. In contrast, if the customers want to minimize the probability of high delay, the value of μ can be set accordingly. But in all cases, the stopping policy is obtained to minimize the cost without bearing an extra delay. Otherwise, the proposed algorithm remains unaffected.

or maximize a payoff. Because the problem is to choose a time slot to stop to minimize the expected cost or to maximize the reward based on randomized decision variables or processes. It means that you have to choose a stopping probability depending on the given observations.

The optimal time slots, stopping price, and schedule load patterns are then used as input parameters to the GA (Part 2, 3) to generate the dynamic electricity price signal for each customer. Where the pricing signal remains fixed for the scheduling period (1 h). As discussed above, the OSR is a pure threshold policy and can provide the best results if supported by mathematical models. In contrast, the electricity price is generally calculated based on the aggregated load demand over a certain period. However, the load consumption patterns are changing over discrete time, therefore, the heuristic-based GA is used to find the optimal pricing policies. Fig. 3 shows the implementation flow of the proposed algorithms. Part 1 represents the OSR-based implementation in finding the optimal schedules and respective costs. While part 2 describes the steps in finding the dynamic pricing policies subject to constraints and limits. Furthermore, to ensure the optimality condition, the final results are compared with the total cost of the load. The zero difference between the scheduled and unscheduled costs reflects that the optimal results are deceived.

6. Simulation setup

For simulations, the data set is obtained from solar home electricity, Ausgrid (Solar, 2021) and built-in algorithms are used for real-time prediction using MATHEMATICA (WOLFRAM MATHEMATICA, 2022). Fig. 2 shows the forecasted profiles obtained from MATHEMATICA that are used as input to the GAMS tool for load scheduling optimization. Because the GAMS is a high-level platform for modeling large-scale industrial problems using optimization & mathematical programming. Its built-in language compiler consists of a variety of solvers such as CPLEX, BORON, CONOPT, LINDO, BORON, etc. Therefore, the modeling language used in GAMS allows modelers to translate real-world optimization problems into machine-readable code. Then GAMS language compiler translates this code into a format that solvers can easily understand. Furthermore, this architecture is highly flexible such that it allows users to change the solvers without modifying the base model. Finally, MATLAB is used for data visualization and data handling.

6.1. Results and discussion

Fig. 4 shows the prediction results using 1D numerical data with confidence interval. In this work, we have used the Gaussian process, linear regression (LR), NN, and ANN to analyze the performance in terms of fast convergence. Results reveal that the Gaussian process and nearest neighbors efficiently handle non-linearities in data. Therefore, the Gaussian method has produced smooth predictors, while the NN has produced non-smooth predictors. Table 1 gives the numerical performance comparison of different machine learning algorithms regarding performance metrics. It can be observed the NN has comparatively fast training time, utilized less memory, and low evaluation time of a single example. However, it has a high batch evaluation time due to the evaluation of the nearest branches. Whereas, the Gaussian process has a low evaluation speed, and high single evaluation time. Finally, the ANN shows high training time, consumes more memory, and has an almost negligible loss. In conclusion, the neural network can give the best results, however, based on high computational complexity and memory.

Fig. 5 shows the electricity price variation factor $\lambda^d(t)$, Eq. (22) based on load demand Eq. (13) and stopping price Eq. (23). This variation well described that the dynamic electricity price for each load i is changing regarding variation in load demand, market-based electricity price signal, and the overall variation in per hour load demand. However, the proposed optimization module does not alter the original electricity price signal $\lambda(t)$ in Eq. (22). Fig. 6 shows the proposed electricity price signal which is dynamically changed over t for each i reflecting the price variation. Unlike DA-RTP which is rather static over 24 h, the proposed price signal varies based on real-time load demand consumption. Consequently, each user/load has been scheduled to reduce the total cost and individual cost of each user specifically. Simulation results also show that the proposed algorithm schedule the load without violating duty cycle requirements to minimize the cost and discomfort. Furthermore, the load is also scheduled in such a way to reduce the overall cost without compromising end-user comfort in terms of power supply and scheduling delays due to electricity price variation. In other words, the load demand and supply are balanced. Besides, the scheduled time slots are obtained from the proposed mechanism based on the duty cycle and social welfare requirements. Furthermore, as it is difficult to manage all the load with customer priority, therefore, the proposed work has introduced a priority to model a delay/social welfare cost to better manage the load demand. In contrast, the

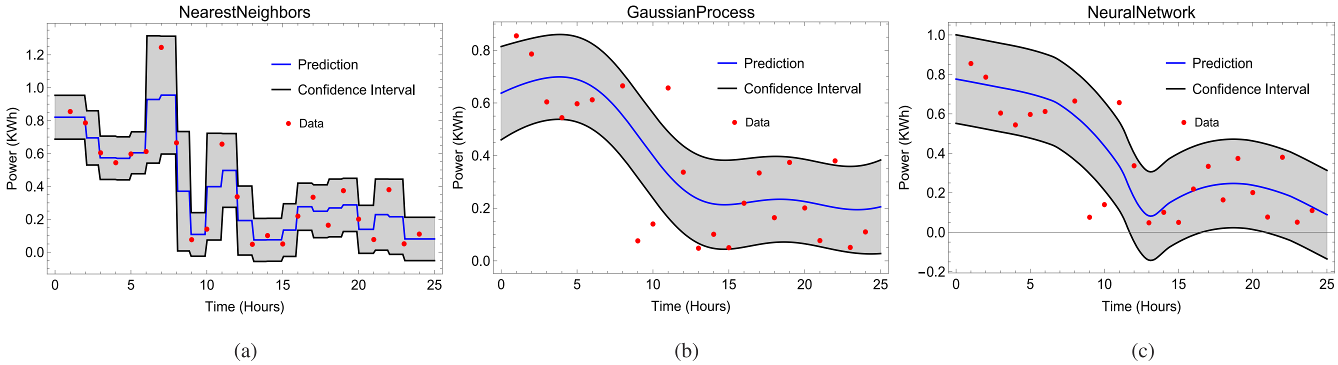


Fig. 4. A comparison of real-time prediction of variable energy resource (Solar, 2022) using ML algorithms over the period of 24 h.

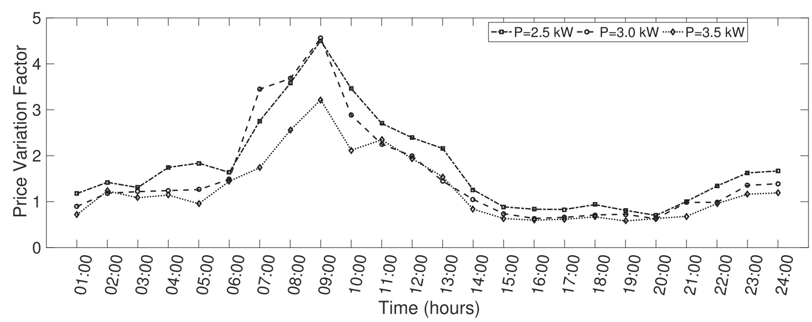


Fig. 5. Electricity price variation factor against each load based on the optimal stopping price obtained from the first step optimal solution.

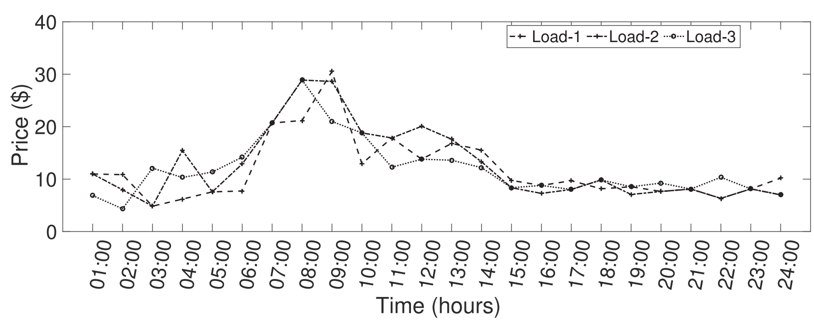


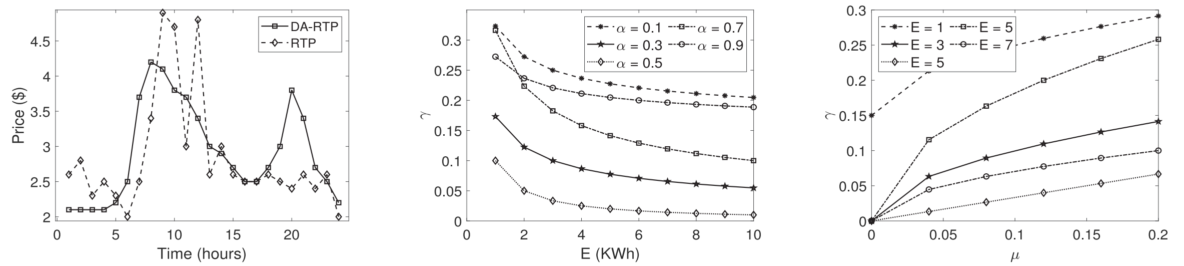
Fig. 6. A new dynamic electricity price signal for each load or user based on the second step optimization (GA).

Table 1
A performance comparison of different machine learning algorithms.

Predictor information			
	Gaussian	Nearest Neighbors	Neural Networks
Data type	Numerical	Numerical	Numerical
Standard deviation	0.314 (±0.11)	0.396 (±0.13)	0.251 (±0.14)
Single evaluation time	5.6 ms/example	3.14 ms/example	3.87 ms/example
Batch evaluation speed	21.6 example/ms	62.5 example/ms	15.2 example/ms
Loss	1.40 (±1.9)	0.551 (±0.56)	0.136 (±0.57)
Model memory	130 kB	113 kB	220 kB
Training example used	17	17	17
Training time	758 ms	302 ms	4.42 s

load can still be managed with the expensive generation which can add more burden on end-users regarding electricity cost.

Fig. 7a shows the comparison of DA-RTP and RTP signals. Where the DA-RTP is generally obtained from NYISO which is known in advance. However, the proposed work has rather used the RTP which is uniformly distributed over the maximum and minimum limits which are [4.971.01] $/KWh. This work has considered the RTP signal with uncertainties to develop a realistic load scheduling algorithm using OSR. Fig. 7b shows the relationship between threshold Eq. (35) and energy consumption which reflects that γ is inversely proportional to the energy demand. Where, the value of γ decreases with the increase in load demand, that will eventually affect the decision process. Fig. 7c shows the relationship between the threshold γ and

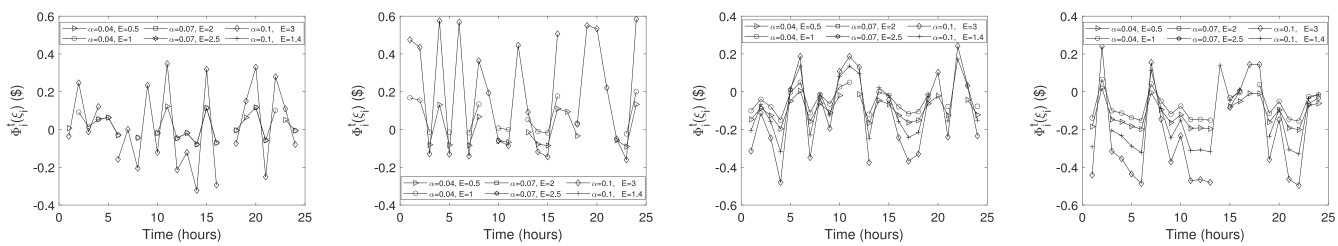


(a) A comparison of electricity price profiles.

(b) Threshold as a function of energy consumption with dynamic probability.

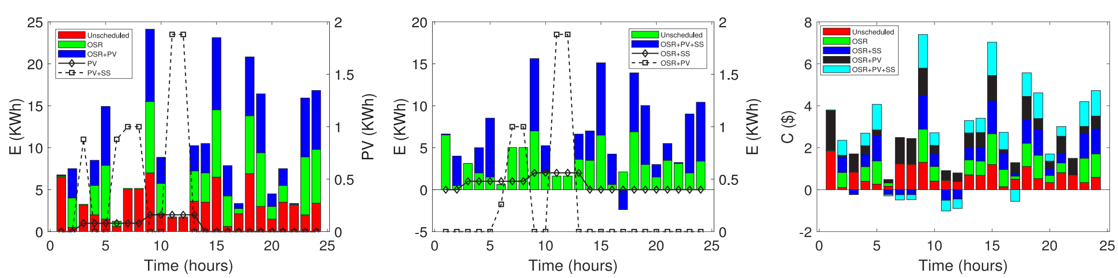
(c) Threshold as a function of dynamic probability μ with dynamic energy demand.

Fig. 7. A comparison of electricity price and threshold profiles of different loads over the period of 24 h.



(a) $\mu(0.1-1.4)$ (b) $\mu(0.04-0.1)$ (c) $\mu(0.001-0.03)$ (d) $\mu(0.001-0.03)$

Fig. 8. A comparison of scheduling delay cost profiles of the loads against different values of (μ) and (α) over the period of 24 h. Different values of μ in (a) and (b) show the impact on scheduling delay cost, which is dynamically changed. (c) and (d) have the same values of μ, however, the scheduling delay cost is again dynamically changed despite having the same value. This is due to uncertainty and randomness during scheduling and decision-making.



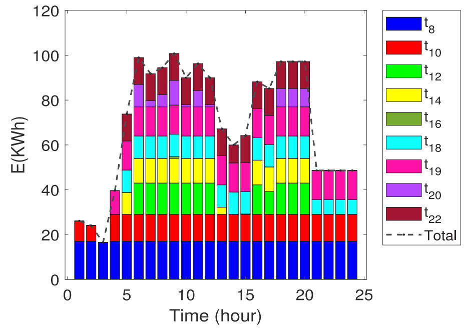
(a) (b) (c)

Fig. 9. A comparison of energy consumption and cost profiles of different loads over the period of 24 h.

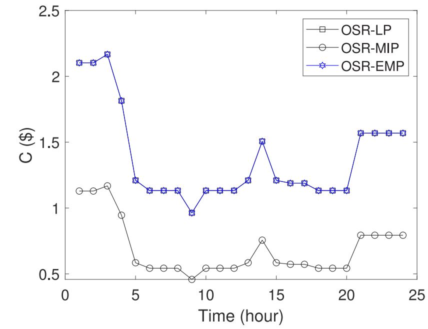
probability/time-factor μ which explains the threshold values γ increases if μ increases and vice versa. In other words, Fig. 7a,b shows that stopping criteria in OSR depends on Eq. (35).

Fig. 8 shows the delay cost profiles over the time t. It is observed that the delay cost also dynamically changes with the probabilities μ, energy demand $ed_i(t)$, Eq. (13) and arrival rate $\alpha_i(t)$, Eq. (17), respectively. Furthermore, Fig. 8c,d show different delay costs with the same probability. Actually, the difference is reflected due to dynamic behavior in electricity cost (RTP), the dynamic cost (Part 2 in Fig. 3), and optimal stopping time based on OSR (Part 1 in Fig. 3) where the cost and scheduling delay are found minimum and other endogenous control variables in OSR and GA, respectively. In response, the delay cost will always be different in each time slot (t) reflecting the dynamically changing behavior of different control parameters. In contrast, if the delay cost and other profiles remain fixed for the given interval (t), means the algorithms have hard constraints and are not updated in regard to other control variables. Fig. 9 shows the cost profiles of different loads i over time t. Generally, these types of cost profiles represent more realistic optimization behavior despite those observed in realistic scheduling. During implementation, the power obtained from the grid source is reduced when a sufficient amount of renewable & storage capacity is available. Because the renewable & storage units act as the first choice to reduce the overall cost and carbon footprints. For example during (t_{11} − 12) in Fig. 9a, the sufficient amount of storage capacity is available due to a demand reduction. This is generally due to the higher electricity price during these time slots. Therefore, surplus energy can be stored and utilized when either the demand capacity is increased or the electricity price is increased.

Similarly, Fig. 9b shows the scheduled and unscheduled load profiles with the integration of storage units. It can be seen that OSR had efficiently managed the load demand without heavily relying on grid energy source $e_g(t)$. Fig. 9c shows the non-smooth



(a) Energy consumption scheduling profiles based on upper limits over 24 time period



(b) Energy consumption cost profiles over 24-hour scheduling period.

Fig. 10. A comparison of energy consumption and cost profiles using LP, MIP, and EMP techniques for 24 h. In Eq. (16), if we impose lower and upper limits Eqs. (25) & (26) during scheduling process, the overall cost is reduced. However, the Φ_ξ is compromised, that depends on the value of $\overline{\Phi_i(t)(d_i(t))}$. This work considers the dynamic value of $\overline{\Phi_i(t)(d_i(t))}$ to better schedule the load in cost-efficient time slots. Otherwise, the static value of $\overline{\Phi_i(t)(d_i(t))}$ may lead to inefficient load distribution as load demand is also dynamic.

cost profile. The cost seems relatively higher during the high demand period or when the renewable & storage capacity is insufficient to fulfill the total demand. On the other hand, the negative cost profile reflects that the surplus energy is stored or sold back to the utility to reduce the overall cost. Furthermore, the irregular and non-smooth cost profiles show noticeable variations due to dynamically changed control variables (see Eqs. (13), (17), (22), (35)). Because, unlike DA-RTP, this work relies on the real-time values parameters. Besides most of the previous works on load schedules are developed based on day-ahead pricing information. To further analyze the algorithmic behavior in handling uncertain variables, this work implements different algorithms such as LP, MIP, and EMP as shown in Fig. 10. It can be seen that LP and EMP have generated almost the same cost profiles. However, the cost profiles are different in MIP technique. This is because, without any quadratic constraints, the objective function is generally solved using the classic branch-and-bound algorithm.

7. Conclusion

The load scheduling problems integrated with renewable energy and storage systems have involved different uncertain control variables and therefore become quite challenging to design. To overcome this problem, the proposed work used a bi-level load demand scheduling mechanism in conjunction with renewable and storage systems. Initially, the mathematical models for the load, scheduling delay, stopping criteria, electricity price, renewable energy, and storage system were developed. Furthermore, the load demand data obtained from Ausgrid solar home is forecasted using real-time ML algorithms (i.e., ANN, NN, & Gaussian Process). Then the first level optimization problems are formulated with the objective of energy consumption cost and scheduling delay minimization. Where the bi-objective optimization function is solved using mathematical programming (i.e., LP, EMP, and MIP) with branch-and-cut and branch-and-bound algorithms. Then the first-level load scheduling problem is further modified to integrate the dynamic electricity pricing mechanism with the objective of cost minimization of each customer through an individualized pricing signal. Since the DA-RTP signal is highly uncertain and depends on the load demand consumption and other endogenous & exogenous control variables. Therefore, the second-level scheduling problem is formulated as a stochastic optimization problem which is solved using GA. As a result, each customer is provided with a separate electricity pricing signal based on his load demand without violating retailer or other customers' objectives.

CRediT authorship contribution statement

Muhammad Babar Rasheed: Conceptualization, Methodology / Study design, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **María D. R-Moreno:** Conceptualization, Methodology / Study design, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Kelum A.A. Gamage:** Conceptualization, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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