Multi-objective Preemptive Optimization of Residential Load Scheduling Problem Under Price and CO_2 Signals

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Abstract

This paper addresses the residential load scheduling problem with the objective of investigating the influence of price and CO_2 signals in (i) the electricity bill, (ii) the consumer inconvenience, (iii) the electric peak load, and (iv) the CO_2 emissions. These objectives were considered widely in the literature; however, they were not considered simultaneously in one model before. Furthermore, CO_2 emissions targets constraint was not considered in the previous literature. This paper contributes by twofold. First, the CO_2 signal is drawn up based on the proposed generation-mix plan in South Africa and an hourly CO_2 emissions limit is guaranteed. Second, a multi-objective mixed integer programming model is proposed, and a preemptive multi-objective optimization approach is applied. The model is tested with and without considering the hourly CO_2 emissions limit. Furthermore, the model is solved at four scenarios to explore the effect of the price and CO_2 signals and the order of optimization. Results showed that the price and CO_2 signals and the order of optimization have remarkable effect on the appliance schedule and on the four objectives.

Keywords
Residential load scheduling, electrical peak load reduction, inconvenience, CO_2 emissions, multi-objective mixed integer programming

1. Introduction
Carbon Dioxide (CO_2) emissions are increasing exponentially all over the world. For example, the total CO_2 emissions in South Africa recorded a dramatic increase of around 400% from 98 million tons in 1960 to 490 million tons in 2014 (The World Bank 2018). Figure 1 shows the total CO_2 emissions profile in South Africa from 1960 to 2014 (The World Bank 2018).

One of the main sources of CO_2 emissions in South Africa is the electricity sector due to the continuous expansion in electricity generation capacity. According to the Integrated Resource Plan for electricity sector in South Africa 2010-2030 (IRP-2010) (DoE SA 2013), the electricity sector generates around 45-50% of national CO_2 emissions. In 2013, the electricity sector generated around 266 million tons of CO_2 emissions in South Africa and this number is expected to climb to 319 million tons in 2025 (DoE SA 2013).

South Africa has set a target to limit CO_2 at 550 million tons per annum starting 2025, which makes eliminating CO_2 emissions a critical and urgent issue (DoE SA 2013). Thus, the CO_2 emission target for the electricity sector in South Africa is established as 275 million tons per annum in the IRP-2010.

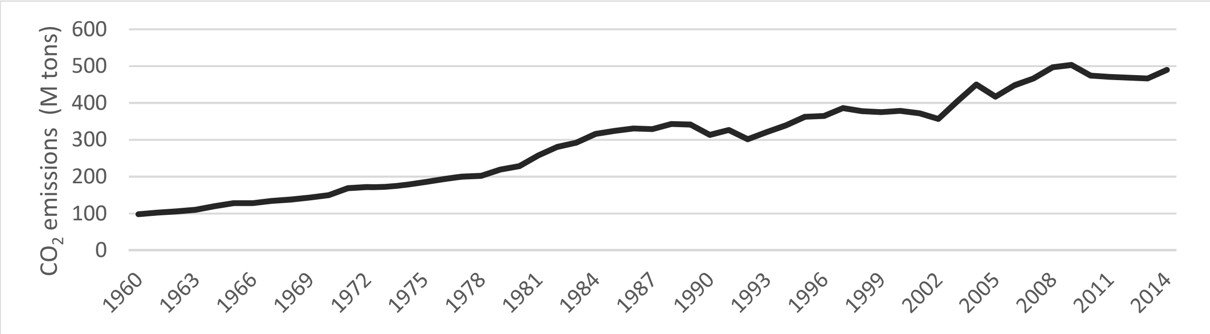

Figure 1. CO_2 emissions profile (million tons) in South Africa.

The residential or domestic sector contributes significantly in the total electricity consumption. Generally, it accounts for around 30~40% of the total energy use all over the world (Torriti 2014). For example, it represents around 20~25% of South Africa's total load. Furthermore, it is a significant contributor to both the morning and evening peak periods (ESKOM 2018).

Demand Response (DR) is one of the solutions to control the peak demand and significantly reduce energy consumption in the residential sector (Sæle and Grande 2011). Naturally, effective DR policies require smart appliances, which can be switched on or off in response to price signal. Similarly, an hourly CO_2 intensity signal could give customers an extra environmental motivation to shift or reduce loads as it would enable minimization of electricity consumption cost and CO_2 emissions.

Several studies have studied the Residential Load Scheduling Problem (RLSP) under time-varying price signal by rescheduling smart appliances. Whilst many authors studied the RLSP under a price signal, few of them guaranteed consumer convenience and preferences in their models' constraints (Sou et al. 2011, Baldauf 2015 and Yao et al. 2016). Furthermore, few authors solved the RLSP with consumer convenience related objective functions. Setlhaolo et al. (2014), Setlhaolo and Xia (2014) and Setlhaolo and Xia (2015) proposed a non-linear optimization model for the RLSP with a bi-objective function that minimizes electricity costs and inconvenience. However, the proposed model formulation was nonlinear which raised the issue of complexity and computation time. Furthermore, few studies considered minimization of peak load and cost simultaneously (Nan et al. 2018, Rasheed et al. 2015, Haider et al. 2014, İzmitligil and Özkan 2016, and Shakouri and Kazemi 2017). However, the aforementioned work considered minimization of either the inconvenience or the peak load; and did not consider these two objectives simultaneously.

Other works have focused on CO_2 emission factors and its potential impacts on the changes in household load profile. Favre and Peuportier 2014 and Paridari et al. 2014) solved the load scheduling problem with the bi-objective function of electricity bill and CO_2 emissions minimization. Paridari et al. (2016) extended their work by considering uncertainty and unpredictable changes in the user preferences with the aim of reducing both the electricity bill and the CO_2 emissions. Rayati et al. (2015) addressed the RLSP while aiming to minimize the electricity and gas bill, consumer dissatisfaction and CO_2 emission cost. Setlhaolo and Xia (2016) studied the RLSP with a dedicated photovoltaic and storage system. They demonstrated that the consumer's preferences, inconvenience and CO_2 emissions objectives could affect the consumption pattern. However, a CO_2 signal-based load shifting was not considered in the aforementioned work.

Few authors considered CO_2 signal while solving the RLSP. Sou et al. (2013) studied the RLSP and investigated the conflict between minimization of electricity bill and CO_2 emission goals. They concluded that the two signals could lead to very different appliances schedules with drastically different electricity bill and CO_2 emission. Song et al. (2014) investigated the joint influence of price and CO_2 signals in a DR program. The results showed that consumers' attitude to the signals largely affect the load shift, bill saving and CO_2 emission reduction. Stoll et al. (2014) tested the effect of electricity price and CO_2 signals on CO_2 emissions, and indicated that the CO_2 signal can help avoid CO_2 emissions increment. However, they did not consider the consumer convenience and preferences, the peak load reduction objective, and CO_2 emissions limits in their study.

Two important gaps are outlined from the review of the literatures. First, the objectives of minimizing the Electricity Bill (EB), the consumer Inconvenience (IC), the Electric Peak Load (EPL) and the CO_2 emissions were considered widely in the literature. However, they were not considered simultaneously before. Second, there is a global concern about the individual national emission commitments, pledges, targets, policy and actions to reduce their greenhouse gas emissions. However, CO_2 emissions targets constraint was not considered earlier in the literature.

This paper deals with these gaps by proposing a Multi-Objective Mixed Integer Linear Programming (MOMILP) model for the RLSP. The proposed model aims to minimize the EB, the IC, the EPL and the CO_2 emissions objectives. Appliance load scheduling is based on both tariff and CO_2 intensity signals. The proposed model considers an hourly CO_2 emissions limit. The paper investigates the influence of applying the tariff and CO_2 intensity signals on the resulted power profile. Furthermore, the effect of considering the hourly CO_2 emissions limit on the four objectives is explored.

The remainder of this paper is organized as follows: Section 2 focuses on defining the problem and presenting the proposed MOMILP optimization model. Section 3 introduces a case study based on a typical household in South Africa and all the data used in this paper. Results, comparisons and discussions are presented in section 4. Lastly, a conclusion is drawn.

2. The proposed mathematical model

The load scheduling problem is concerned with the selection of an optimal on/off status of each home appliance over the day that minimizes the EB, the IC, the EPL and the CO_2 emissions. Due to the conflict between the considered objectives, the multi-objective preemptive approach is applied to solve the proposed model. Two demand response signals are considered in this paper: (i) TOU electricity tariff, and (ii) CO_2 intensity. A sampling time (Δt) of 10 minutes and a study period of 24 hours (full-day) are considered in the proposed model. Table 1 summarizes the indices, parameters and decision variables used in this paper.

Table 1. Notation summary

Notation	**Description**
Indices:	
$i \in I$	Index of home appliance, *I* is the total number of appliances.
$t \in T$	Index of time/ time slot, $t = 1, \ldots T$, where *T* is the horizon, which is 24 h.
Parameters:	
P_i	The rated power (KW) of appliance *i*.
N_i	The required number of time slots (Slot) to complete the normal operation of appliance *i*.
S_i	The start of the time interval (Slot number) in which the appliance *i* is to be scheduled.
E_i	The end of the time interval (Slot number) in which the appliance *i* is to be scheduled.
C_t	The electricity price (R/KWh) at time *t*.
V_t	The incentive offered (R/KWh) at time *t*.
Δt	The sampling time (Minutes).
Q	The maximum cost (R) that the consumer is willing to incur in one day.
$X_{i,t}$	A binary parameter represents consumer's preferred/baseline ON/OFF status of appliance *i* at time *t*
R_t	The CO_2 emission rate at time *t* (Kg/KWh).
CO_2HL	The hourly limit of the CO_2 emissions (Kg/hr).
Main decision variables:	
$x_{i,t}$	A binary variable represents the optimal ON/OFF status of appliance *i* at time *t*.
Auxiliary decision variables:	
$z_{i,t}$	A binary indicator function for inconvenience.
$y_{i,t}$	A binary indicator function for incentives.
$u_{i,t}$	A binary indicator function to guarantee uninterruptible operation.

l_t	A real value represents the total consumed electrical power or load (KW) at time *t*.
EPL	The maximal electrical peak load (KW) over the study period *T*.

2.1. Model objective functions

The objective functions in the multi-objective RLSP can be formulated as follows:

2.1.1. The first objective function: minimizing the electricity bill (EB)

One of the main objectives of an electricity-consuming household is to minimize its electricity bill. To achieve this, appliances should be scheduled to benefit from the lower electricity prices offered during peak times. To minimize the EB through these incentives, the first objective function is characterized by two components: the electricity cost and the incentives offered.

$$Min\ F_{EB} = \sum_{t=1}^{T}\sum_{i=1}^{I} P_i \cdot \left[C_t \cdot x_{i,t} - V_t \cdot y_{i,t}\right] \cdot \Delta t \tag{1}$$

Where, t is the time index, t = 1, ... T, Δt is the sampling time and T is the horizon, which is 24 h. i is the appliance index, i = 1, ... I, and I is the total number of appliances. P_i is the rated power of appliance i. C_t is the electricity price at t and V_t is the incentive at t. $x_{i,t}$ is the optimal/new ON/OFF status of appliance i at time t. Where, $x_{i,t} = 1$ if appliance i is scheduled to be ON at time t and $x_{i,t} = 0$ if appliance i is scheduled to be OFF at time t. $y_{i,t}$ is a binary indicator function that allows consumers to earn an incentive. Consumers earn incentives only when they switch off their appliances during peak times. If $y_{i,t}$ is 1, an incentive is earned, otherwise there is no incentive.

2.1.2. The second objective function: minimizing the inconvenience (IC)

Consumer's conveniences may be the most important objective of an electricity-consuming household. The objective to minimize scheduling inconveniences seeks to minimize the disparity between the preferred and the optimal schedule. In this research, postponement and advancement of the schedule are both regarded as the inconvenience.

$$Min\ F_{IC} = \sum_{t=1}^{T}\sum_{i=1}^{I} z_{i,t} \tag{2}$$

Where $z_{i,t}$ is a binary indicator function to make the obtained schedule suffer an inconvenience penalty when the obtained schedule does not match the consumer's preferred schedule. If it is 1, an inconvenience penalty is charged, otherwise there is no inconvenience penalty.

2.1.3. The third objective function: minimizing the electricity peak load (EPL)

The third objective function minimizes the hourly electricity peak/maximal load over the day. It seeks to level the hourly load profile resulting from the optimal schedule. Thus, this is a min-max objective. Where, the value of EPL is calculated based on constraints (7-8).

$$Min\ F_{EPL} = EPL \tag{3}$$

2.1.4. The fourth objective function: minimizing the CO2 emissions (CE)

The fourth objective function emphasizes the CO_2 emissions due to the household electric consumption. It targets to shift the electric loads according to the hourly CO_2 emissions rate (Kg of CO_2 emissions/KWh). Thus, it aims to minimize the total daily CO_2 emissions.

$$Min\ F_{CE} = \sum_{t=1}^{T}\sum_{i=1}^{I} R_t \cdot P_i \cdot x_{i,t} \cdot \Delta t \tag{4}$$

Where R_t is the hourly CO_2 emissions rate (Kg of CO_2 emissions/KWh).

2.2. Model constraints

The model constraints are formulated as follows.

$$X_{i,t} - x_{i,t} \leq y_{i,t} \qquad \forall i \in I, \forall t \in T \qquad (5)$$

$$X_{i,t} - x_{i,t} \leq z_{i,t}$$
$$x_{i,t} - X_{i,t} \leq z_{i,t} \qquad \forall i \in I, \forall t \in T \qquad (6)$$

$$l_t = \sum_{i=1}^{I} P_i \cdot x_{i,t} \qquad \forall t \in T \qquad (7)$$

$$EPL \geq l_t \qquad \forall t \in T \qquad (8)$$

$$\sum_{i=1}^{I} R_t \cdot P_i \cdot x_{i,t} \cdot \Delta t \leq CO_2HL \qquad \forall t \in T \qquad (9)$$

$$\sum_{t=1}^{T} \sum_{i=1}^{I} P_i \cdot [C_t \cdot x_{i,t} - V_t \cdot y_{i,t}] \cdot \Delta t \leq Q \qquad (10)$$

$$\sum_{S_i}^{E_i} x_{i,t} \geq N_i \qquad \forall i \in I \qquad (11)$$

$$x_{i,t} \leq 1 - u_{i,t} \qquad \forall i \in I, \forall t \in T$$
$$x_{i,t-1} - x_{i,t} \leq u_{i,t} \qquad \forall i \in I, \forall t \geq 2 \qquad (12)$$
$$u_{i,t-1} \leq u_{i,t} \qquad \forall i \in I, \forall t \geq 2$$

$$x_{i,t} \leq u_{\bar{i},t} \qquad \forall t \in T \qquad (13)$$

Constraint (5) sets the value of $y_{i,t}$ as 1 if consumers switch off their appliances in an anti-preference way. Thus, $y_{i,t}$ =1 if ($X_{i,t}$ - $x_{i,t}$) is greater than zero, otherwise $y_{i,t}$ = 0. Whereas, $X_{i,t}$ is the consumer's preferred/baseline ON/OFF status of appliance *i* at time *t*. $X_{i,t}$ = 1 if consumer prefers appliance *i* to be ON at time *t* and $X_{i,t}$ = 0 if consumer prefers appliance *i* to be OFF at time *t*.

Constraint (6) sets the value of $z_{i,t}$ as 1 if the obtained schedule does not match the consumer's preferred schedule ($X_{i,t} \neq x_{i,t}$). Thus, the inconvenience term can be modeled using the absolute value of the difference between the preferred and the optimal schedules as, $z_{i,t} = |X_{i,t} - x_{i,t}|$. However, the absolute function linear equivalent is used.

Constraint (7) calculates the load profile l_t as the sum of the power consumption due to all the scheduled appliances at time *t*.

Constraint (8) aims to find the maximal/peak electric load over the day horizon (*T*) which can be modeled using the maximal value of l_t as ($EPL = max\ l_t$). However, the maximal function linear equivalent formulation is used. The linear formulation implies that the *EPL* exceeds each l_t which ensures that the objective function minimizes the maximal/peak load.

Constraint (9) calculate the CO_2 emissions at each time slot *t* from all appliances and guarantees that the produced emissions do not exceed the defined CO_2 hourly limit (CO_2HL).

Constraint (10) guarantees that the appliance schedule is bound by the maximum amount that the consumer is willing to incur in one day (*Q*).

Constraint (11) guarantees that the assigned time slots for each appliance are within interval [S_i, E_i] and are sufficient to execute the appliance operation.

The set of constraints (12) ensures uninterruptible operation of appliances. This ensures that the assigned time slots for each appliance are successive. This can be modeled by guaranteeing that $x_{i,t}$ = 0 if there exists an earlier time slot

$\tilde{t} < \tilde{t} + 1 < t$ such that $x_{i,\tilde{t}} = 1$ and $x_{i,\tilde{t}+1} = 0$. For appliances that may be operated more than one time per day (i.e., oven operation for lunch and dinner), the appliance can be treated as two separate appliances. Where $u_{i,t}$ is a new auxiliary binary decision variable that equals 1 if the operation of appliance i is already completed before time slot t (i.e., the operation of the appliance is just finished). Hence, the corresponding $x_{i,t}$ must be zero and $u_{i,t} = 1$ remain unity.
Constraint (13) guarantees the logical sequence between any two sequential appliance operations. For example, the operation of a clothes dryer follows the operation of the washing machine. Thus, logically, the start of the time interval in which the clothes dryer is to be scheduled ($S_{\text{clothes dryer}}$) should be at least greater than $S_{\text{washing machine}}$ plus $N_{\text{washing machine}}$. This condition can be conveniently described using the main decision variable $x_{i,t}$ and the auxiliary decision variable $u_{i,t}$ as ($x_{i=clothes\ dryer,t} \leq u_{i=washing\ machine,t}$). Where $\tilde{i}$ is the index of the appliance which must be finished before i can start.

2.3. The solution approach

A sequential optimization of individual objectives or the so called "Preemptive optimization approach" is applied to solve the proposed MOMILP optimization model. The preemptive optimization technique realizes that objectives are rarely of equal importance nor have the same dimensions. Therefore, it considers one objective at a time in a sequential way (Rardin 2016). However, the main limitation of this approach is that it does not provide a compromise solution for all objectives. First, it optimizes the most important objective, then it optimizes the second most important objective, subject to a condition that the first objective must achieve its optimal value. This approach is repeated for all objectives.

With multi-objective optimization models, a global optimal solution to the problem cannot be obtained, but rather various efficient solutions are introduced. The order of optimization given to individual objective functions (i.e., 1, 2, 3 and 4) controls the benefits received by consumers and utilities. For the first and second scenarios (section 4), benefits are biased towards consumers by assigning a precedent order of optimization to the EB and the IC, respectively. However, for the third and fourth scenarios (section 4), benefits are biased towards utility companies and environment by assigning a precedent order of optimization to the EPL and the CO_2 emissions, respectively.

For example, based on the order of optimization for the first scenario (section 4), the preemptive approach is applied as follows.

Step 1 – The RLSP is solved with the individual objective function (1), subject to constraints (5) to (13). The optimal objective value of the F_{EB} (EB^*) is obtained.

Step 2 – The RLSP is solved with the individual objective function (2), subject to constraints (5) to (14). A new *constraint* (14) is added to guarantee the bound of the F_{EC} as following, and the optimal F_{IC} (IC^*) is obtained.

$$\sum_{t=1}^{T}\sum_{i=1}^{I} P_i \,.\left[C_t \cdot x_{i,t} - V_t \cdot y_{i,t}\right].\Delta t \leq \; EB^* \tag{14}$$

Step 3 – The RLSP is solved with the individual objective function (3), subject to constraints (5) to (15), including constraint (14). A new constraint (15) is added to guarantee the bound of the F_{IC} as following, and the optimal objective value of the F_{EPL} (EPL^*) is obtained.

$$\sum_{t=1}^{T}\sum_{i=1}^{I} z_{i,t} \leq \; IC^* \tag{15}$$

Step 4 – The RLSP is solved with the individual objective function (4), subject to constraints (5) to (16), including constraints (14) and (15). A new constraint (16) is added to guarantee the bound of the F_{EPL} as following, and the optimal objective value of the F_{CE} (CE^*) is obtained.

$$EPL \leq \; EPL^* \tag{16}$$

The final solution obtained from *Step 4* is an efficient solution for the original multi-objective RLSP.

3. Case study

A typical household in South Africa with ten appliances has been used as a case study. Table 3 provides the model input parameters for each appliance. For example, appliance 1 (Stove) is scheduled twice in a day for 30 and 50 min in the morning and evening, respectively. It is to be switched on at any time between t = 30 (05:00) to t = 42 (07:00) and t = 96 (16:00) to t = 120 (20:00), respectively. Appliance 2 (Microwave) is scheduled once a day for at least 10 min any time from t = 96 (16:00) to t = 114 (19:00). Because the EWH is a continuous on/off appliance, it is excluded from the uninterruptible constraint. The appliance's preferred/baseline schedule is considered based on Setlhaolo et al. (2014).

The optimal appliance schedule is bounded by the maximum cost that the consumer is willing to incur in one day (Q), and an hourly CO_2 emissions limit (CO_2HL). The Q value is assumed to be not more than R25 (R denotes the South Africa currency, ZAR or rand). The Integrated Resource Plan for electricity sector in South Africa 2010-2030 (IRP-2010) established the CO_2 emission target from the electricity sector as 275 million tons per annum (DoE SA 2013). Considering that the residential electricity load represents around 23% of South Africa's total load (ESKOM 2018), the CO_2 emission target from the residential consumers could be assumed as 63.25 million tons per annum. Statistics South Africa (2016) reported that households with access to electricity at 2016 were around 14,795,827. Thus, the CO_2 emission target from a typical household could be assumed as 4,274.85 kg per annum and the hourly CO_2 emission target from a typical household (CO_2HL) is assumed as 0.488 kg.

The tariff used is based on South Africa's TOU tariff for residential consumers. Figure 2 shows that the TOU peak and off-peak tariff are R1.4452/kWh and R0.4554/kWh, respectively. Eskom's peak times are 07:00 – 10:00 and 18:00–20:00 (Eskom Tariffs & Charges 2018). The hourly charge is discretized into a 10-minute sampling time to match the proposed model sampling time, and the optimization is done over a 24-h period. An incentive of V_t = R0.20/kWh was assumed based on Setlhaolo et al. (2014).

Table 2. Appliances data.

No.	Appliance	Power rating, P_i (kW)	Duration, N_i (time slot)	S_i (slot #)	E_i (slot #)	Baseline Schedule (slot #)
1	Stove	3.000	3	30	42	37-39
			5	96	120	108-112
2	Microwave	1.230	1	96	114	108
3	Kettle	1.900	1	33	45	39
			1	106	120	109
4	Toaster	1.010	1	30	42	31
5	Steam iron	1.235	5	96	126	108-112
6	Vacuum cleaner	1.200	3	48	62	54-56
7	Electric water heater (EWH)	2.600	12	24	49	25-36
			12	96	132	105-116
8	Dishwasher	2.500	15	120	144	120-134
9	Washing machine	3.000	5	96	132	111-115
10	Tumble dryer	3.300	3	96	122	120-122

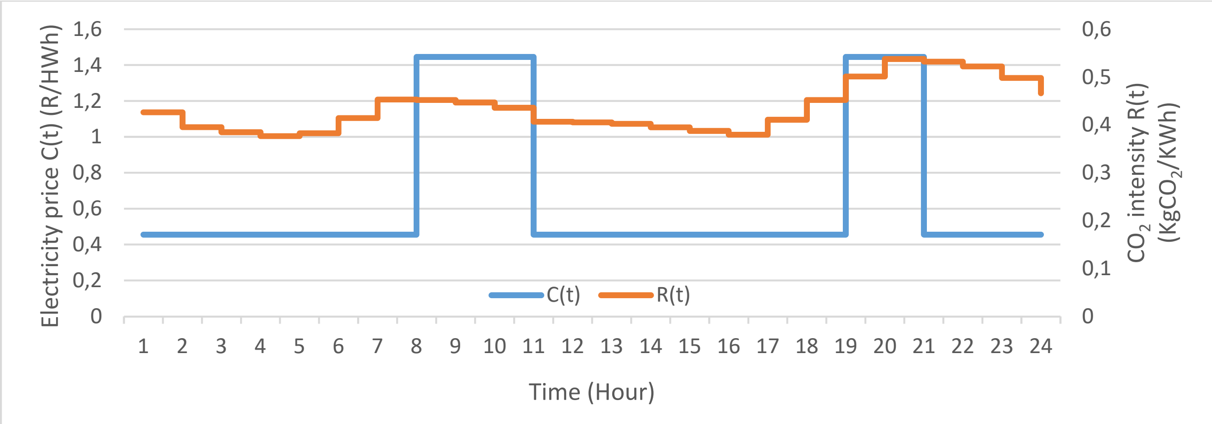

Figure 2. The hourly electricity price and CO_2 intensity in South Africa.

The CO_2 intensity signal used is based on the results reported by Yahia and Kholopane (2019), where an electricity generation-mix on an hourly basis was developed for South Africa based on the electricity sector 2030 plan. The dynamic hourly CO_2 intensity signal is derived based on that hourly electricity generation-mix data (Stoll et al. 2014). Figure 2 shows the CO_2 intensity signal used in this research.

4. Results and discussion

The proposed model is solved optimally with the commercial optimization solver LINGO 12.0 of two different cases. Case 1 ignores the CO_2HL, thus the proposed model is solved without constraint (9). Case 2 respects the CO_2HL while solving the proposed model. This will show how considering the hourly CO_2 emissions target would influence the appliance schedule.

Four scenarios are studied for each of the two cases. Scenario 1 and Scenario 2 focus on the consumer benefits by targeting to minimize the consumer electricity bill and the consumer inconvenience, respectively. To achieve that, a highest order of optimization is assigned to the F_{EB} objective and the F_{IC} objective, respectively. Scenario 3 focuses on the utility company benefits by targeting to minimize the EPL. To achieve that, a highest order of optimization is assigned to the F_{EPL} objective. Scenario 4 concerns about the environmental impact by targeting to minimize the CO_2 emissions by assigning a highest order of optimization to the F_{CE} objective.

In Table 3 — Case 1, high order of optimization on electricity bill (scenario 1) gives the lowest cost of R10.60, while high order of optimization on consumer inconvenience (scenario 2) gives the lowest inconvenience of zero, high order of optimization on electric peak load (scenario 3) gives the lowest peak of 3.30 kW and high value on CO_2 emissions (scenario 4) gives the lowest value of 11.75 kg of CO_2.

Compared to first three scenarios, scenario 4 could reduce CO_2 emissions by around 4%, 11% and 7% respectively. This percentage represents the CO_2 emissions reduction per day for a typical household. In the national level, these percentage represent massive CO_2 emissions reduction of 7,197; 21,482 and 13,082 tons per day, respectively. This translates to a massive CO_2 emissions reduction of 2.6, 7.8 and 4.8 million tons per annum, respectively. However, scenario 4 resulted in a high peak load. This result guided the research to study the effect of considering the CO_2 emissions hourly limit while solving the problem (Case 2).

In Table 4 — Case 2, with applying an hourly CO_2 emission limit and comparing to first three scenarios, scenario 4 could reduce CO_2 emissions by around 4%, 7% and 6%, respectively. In the national level, these percentage represent massive CO_2 emissions reduction of 6,791; 13,464 and 11,120 tons per day, respectively. This translates to a massive CO_2 emissions reduction of 2.5, 4.9 and 4.1 million tons per annum, respectively. In addition, applying an hourly CO_2 emission limit resulted in significant reduction in the EPL. Thus, the proposed model could eliminate CO_2 emissions and reduce the EPL as well.

Table 3. Effect of order of optimization on the four objectives for case 1.

Scenario	Order of optimization				F_{EB} (R)	F_{IC} (Slot)	F_{EPL} (KW)	F_{CE} (Kg)
	F_{EB}	F_{IC}	F_{EPL}	F_{CE}				
1	1	2	3	4	10.60	58	8.74	12.23
2	2	1	3	4	23.06	0	9.84	13.20
3	2	3	1	4	13.99	76	3.30	12.63
4	2	3	4	1	10.60	94	11.07	11.75

Table 4. Effect of order of optimization on the four objectives for case 2.

Scenario	Order of optimization				F_{EB} (R)	F_{IC} (Slot)	F_{EPL} (KW)	F_{CE} (Kg)
	F_{EB}	F_{IC}	F_{EPL}	F_{CE}				
1	1	2	3	4	10.60	60	6.00	12.34
2	2	1	3	4	18.64	22	5.74	12.79
3	2	3	1	4	13.99	76	3.30	12.63
4	2	3	4	1	10.60	96	6.84	11.88

Figure 3 shows the results of the four scenarios for Case 1. It was observed that scenario 1 scheduled all appliances to off-peak in order to reduce the electricity bill. Scenario 2 scheduled all appliances to match the consumer preferred schedule in order to reduce the inconvenience. It was observed that scenario 3 scheduled all appliances while avoiding overlaps of appliances, which resulted in the minimum EPL of 3.3 kW. Scenario 4 scheduled the appliances to the time slots associated with the lower CO_2 emission intensity, as much as possible, to reduce the CO_2 emissions, which resulted in the lowest CO_2 emissions of 11.75 kg of CO_2. Figure 4 shows the power profile resulting from the four scenarios while applying an hourly CO_2 emission limit. It was observed that applying the hourly CO_2 emission limit resulted in leveled power profiles compared to Case 1. Reducing the peak load and levelling the power profile can reduce CO_2 emissions, because the peak load requires marginal electricity generation from more CO_2 intensive generation sources.

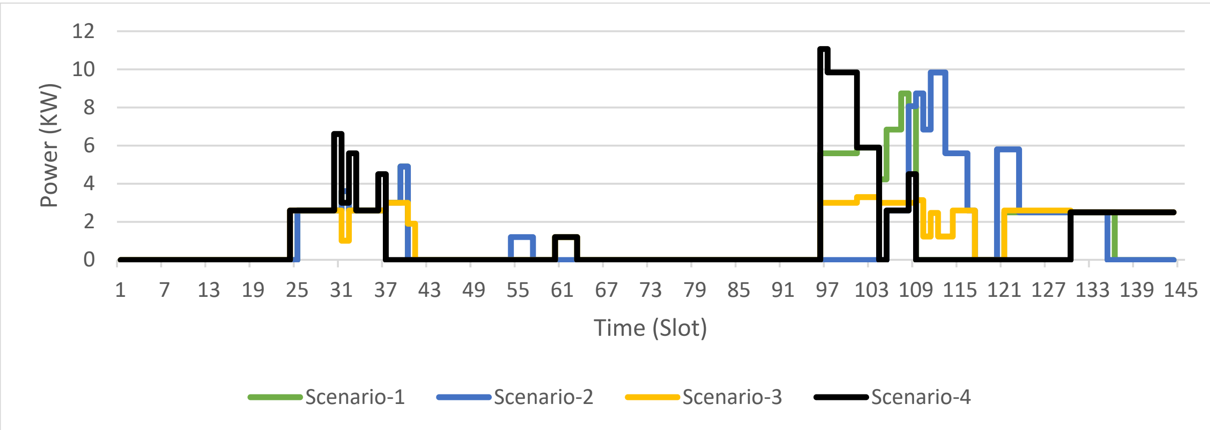

Figure 3. The power profiles under four schedules with different order of optimization for Case 1.

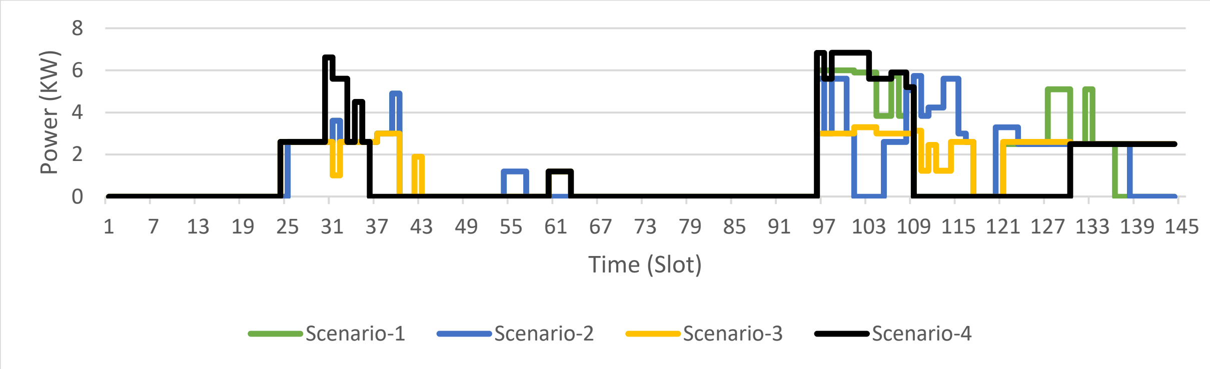

Figure 4. The power profiles under four schedules with different order of optimization for Case 2.

5. Conclusion

In this paper, an MOMILP optimization model is proposed to address the RLSP while considering price and CO_2 signals. The proposed model aimed to optimize appliance load schedules in terms of the EB, the IC, the EPL, and the CO_2 emissions. The model considered an hourly CO_2 emissions limit, which was defined based on the yearly CO_2 emissions target in South Africa. The effect of considering the hourly CO_2 emissions limit was investigated and results showed that applying an hourly CO_2 emission limit could reduce the EPL significantly and could eliminate the CO_2 emissions as well. Furthermore, the effect of the price and CO_2 signals and the order of optimization on the resulting appliance schedules was explored. The price and CO_2 DR signals, and the order of optimization over the four objectives could lead to very different appliances schedules with drastically different EB, IC, EPL and CO_2 emission. These results emphasized that the hourly CO_2 signal could give consumers an extra environmental motivation toward DR programs. Future work may focus on getting more compromise solutions for all objectives by applying different multi-objective optimization approaches, as well as uncertainties in appliance duration is to be considered.

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