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Correlation of multiple time-scale and uncertainty modelling for renewable energy-load profiles in wind powered system

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ABSTRACT

Renewable energies and electrical loads usually show short-term variations in their energy profiles and they need to be precisely modeled in terms of time-scale and uncertainty. Correlation of time-scale, uncertainty, and simulation time must be studied to make an optimal tradeoff between these parameters. This paper aims to deal with this issue and it studies the correlation of time-scale and uncertainty in the renewable energy simulation. The different time scales including 15, 30, and 60 min are modeled and simulated. Uncertainty of electrical loads and wind energy are also incorporated. The introduced model is simulated and investigated on a typical building for energy management. Energy management tool is simulated under multiple time-scale patterns and wind-load uncertainty. The model is expressed as mixed integer stochastic programming and results confirm that considering shorter time-scale results in more precise outputs. It is demonstrated that 30, 15, and 5-min time-scale reduce the cost about 5, 3, and 0.8%, respectively. But they increase the simulation time about 100, 200, and 300%, respectively. As a result, 15-min time-scale is considered as the best case because it keeps both simulation time and model accuracy on the acceptable level. It is also shown that uncertainty in model increases the cost about 22% and reduces load by 10% and decreases the cost about 38%.

1. Introduction

Renewable energy resources (RESs) are cost effective and have been studied in different problems of electrical systems. The power flow (Morales et al., 2010), electricity market (Zhechong and Lei, 2014), network stability (Remon et al., 2017), microgrids (Wang et al., 2018), home energy systems (Keskin Arabul et al., 2017), network expansion planning (Villumsen et al., 2013), unit commitment (Wang et al., 2017), economic dispatch (Azizipanah-Abarghooee et al., 2016) are the well-known problems that have been addressed including RESs. The autonomous and off-grid systems (Yi et al., 2017) often installs RESs to supply their load demand (Maleki, 2018).

Together with developing penetration level of RESs, the demand for short-scale forecasting and modelling of RESs is increased. In this regard, the minute-scale operation is presented as an efficient technique to model wind energy (Würth et al., 2019). The multiple time scale simulation of solar system is addressed by (Chirapongsananurak and Santoso, 2017), where the steady-state, electro-mechanical transient, and electro-magnetic transient are simulated. The short term wind energy forecast is often addressed by optimization methods or neural networks (Li et al., 2018). The solar energy is forecasted by application of statistical methods or artificial neural networks (Sheng et al., 2018). The forecasting not only is applied for RESs but also is used for the other parameters such as electricity prices and loads (Bento et al., 2018).

However, forecasting methods always come with an error and their forecasted data may not match exactly the real data. Such systematic error must be modeled and considered in the problems. This error is known as renewable uncertainty and it is modeled by probability methods (Salkuti, 2019). There are various methods to deal with renewable uncertainty such as stochastic programming, robust programming, point estimated method, chance constrained programming, and fuzzy theory (Peng et al., 2015).

The typical time-scale for simulating electrical energy systems is one hour (60-min). This time-scale is widely adopted to model electrical loading (Mehrjerdi, 2019b), solar energy (Liu et al., 2019),

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Nomenclature

$C_E^{y,t}$	Energy cost ($/kWh)
$f(V_s^{r,y,t})$	Function showing the relationship of wind speed and wind turbine output power
I^t	Duration of time interval (Minute)
I^y	Duration of season (Day)
$P_L^{r,y,t}$	Power of load (kW)
$P_N^{r,y,t}$	Traded power between building and grid (kW)
P_N^{Limit}	Thermal limit of line power (kW)
$P_W^{r,y,t}$	Power of wind turbine (kW)
$P_W^{\max}$	Wind turbine maximum power (kW)
Q^r	Probability of scenario
r, R	Index of scenarios, Set of scenarios
t, T	Index of time intervals, Set of time intervals
$V_s^{r,y,t}$	Wind speed (m/s)
V_s^{ci}	Cut-in speed of wind turbine (m/s)
V_s^{r}	Rate speed of wind turbine (m/s)
V_s^{co}	Cut-out speed of wind turbine (m/s)
y, Y	Index of seasons, Set of seasons
Φ	Annualized energy cost ($/year)

hydro energy (Norouzi et al., 2014), wind energy (Abbey and Joós, 2009), and energy storage systems (Moradi et al., 2017). However, some parameters such as thermal loads needs shorter time-scale modelling. The thermal systems may be modeled with minute-scale models (Pan et al., 2016). The fast-ramping generation system similarly needs time-scale modelling about minutes (Kargarian et al., 2016). The power system operation under such fast ramping RESs are the other systems that models short time scales (Cui et al., 2017). Electric vehicles operation is one of the models that needs short time-scales, e.g., 15-min (Luo et al., 2018; Mehrjerdi and Rakhshani, 2019). The electric vehicle charging stations also operate based on short time-scale models (Mehrjerdi, 2019b).

Considering different time scales for simulating may make impacts on electrical energy systems such as operation of networks, micro-grids (Firouzmakan et al., 2019), home energy management, planning of networks, renewable and energy storage operation, distributed energy storage systems, and mobile modeling of energy resources (Saber et al., 2018).

Energy management system in the buildings is an optimization programming that is thoroughly associated with time-scale modeling of the loads and energy systems (Yang et al., 2019). This tool deals with energy generation and consumption in the building in order to minimizing the energy cost or maximizing efficiency of the available energy resources (Mehrjerdi, 2019a). There are various models and methods to deal with such issues that are presented through home energy management system. The home energy management system has been investigated considering various energy resources (Yang et al., 2018), loads (Beaudin and Zareipour, 2015), uncertainty management methods (Huang et al., 2016), demand response programs (Shirazi and Jadid, 2017) and energy storage systems (Mehrjerdi, 2019c).

1.1. *The knowledge gap and contributions of the paper*

Time-scale and uncertainty are the inseparable and key parameters in the modelling and simulation of RESs and electrical loads. RESs have short-term fluctuations and their performance must be accurately modeled in terms of time-scale and uncertainty. The optimal tradeoff needs to be performed between time-scale, uncertainty, and simulation time. The simulation results without considering such correlations may not match the realistic. In order to address these issues, this paper presents and analyses the multiple time-scale models for simulation of electrical energy systems. The purpose is to demonstrate the impacts of time-scale modelling on simulation of the energy systems. A building equipped with electrical load and wind turbine is developed as test case. The daily profile for electrical load, wind energy, and electricity price is modeled based on 24-h period. Three different time scales are adopted and simulated including 15, 30, and 60-min. The uncertainties of the loads and wind energy are incorporated in the model through stochastic programming. The annualized energy cost of the building is minimized considering the proposed time-scale patterns and uncertainties. The model is expressed as mixed integer stochastic programming and solved by GAMS software. The numerical results verify that the time-scale is an efficient parameter to model the energy-load profiles and considering shorter time-scale provides more precise results. The correlation between time-scale and uncertainty is also investigated.

The main contributions of the paper are highlighted as follows;

- ✓ Investigating the correlations of time-scale, uncertainty, and simulation time.
- ✓ Finding optimal model to keep both time-scale and simulation time on the acceptable levels.
- ✓ Simulating the RESs and electrical loads by the given mode.
- ✓ Simulating the derived model on a typical test system.

2. Multiple time-scale model

The proposed concept presents the flexible time-scale modelling for energy and load profiles. As shown in Fig. 1, there are three different time-scales to model the daily profile. The first time-scale uses 60-min time intervals. In this model, the system is not flexible and it is not possible to model the short term alterations of the loads and energy systems. The second approach uses 30-min time intervals and brings more flexibility to the model. The last item models the daily profile by 15-min time intervals. All the introduced paradigms have been used in the electrical systems to model

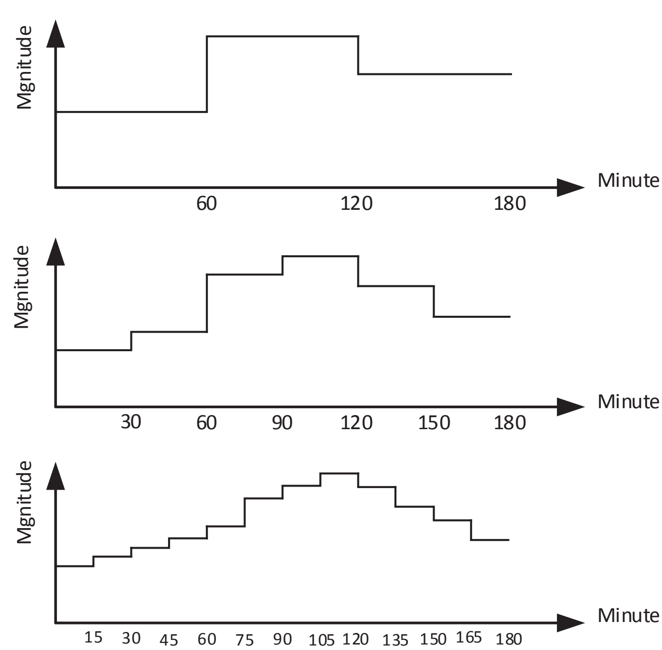

Fig. 1. Various time-scale modelling for simulation of loads and energy systems.

the loads and energy profiles. Their accuracy is simulated and studied in the current paper through proper comparison (Würth et al., 2019).

One of the main issues related to the time scale modelling is uncertainty. The load and energy profiles are forecasted based on the historical data. But the forecasted data always include errors. Considering shorter time scale profiles for forecasting often provides more errors but considering wider periods such as one-hour time scale may provide less errors. This systematic error must be modeled and considered in the problems. As a result, it is useful to evaluate the impacts of time-scale modeling and uncertainty on each other. In this respect, this paper models the correlation of time-scale and uncertainty in simulation of RESs and loads. In order to show the impacts of time-scale modeling on the problem, three different time-scales are modeled and uncertainties of loads-wind energy are incorporated.

3. Problem under multiple time-scale

The correlation of uncertainty and time-scale is modeled in the building powered by wind energy. The annualized energy cost of the building is calculated by (1). Both uncertainty and time-scale are included in the model and they are influential parameters of the system (Hemmati, 2017).

$$\Phi = \sum_{r\in R}\sum_{y\in Y}\sum_{t\in T}\left(P_N^{r,y,t} \times I^t \times C_E^{y,t} \times Q^r \times I^y\right) \tag{1}$$

The daily profiles are simulated under 24-h period. As a result, sum of all time intervals during one day must be equal to 24 h as indicated in (2).

$$\sum_{t\in T} I^t = 24 \quad \forall y\in Y \tag{2}$$

The building is connected to the electrical network by tie-line. The traded power between the building and electrical network is modeled in (3); where, the wind and load powers are positive variables as shown through (4) and (5) (Hemmati and Saboori, 2017).

$$P_N^{r,y,t} = P_L^{r,y,t} - P_W^{r,y,t} \quad \forall r\in R, y\in Y, t\in T \tag{3}$$

$$P_W^{r,y,t} \geq 0 \quad \forall r\in R, y\in Y, t\in T \tag{4}$$

$$P_L^{r,y,t} \geq 0 \quad \forall r\in R, y\in Y, t\in T \tag{5}$$

Power between building and grid can be positive or negative as shown in (6). The negative values mean that the building sends energy to the network (Hemmati and Saboori, 2017).

$$-P_N^{Limit} \leq P_N^{r,y,t} \leq +P_N^{Limit} \quad \forall r\in R, y\in Y, t\in T \tag{6}$$

The probability of all scenarios in the model must be equal to one as specified by (7) and the wind power is modeled as (8).

$$\sum_{r\in R} Q^r = 1 \tag{7}$$

$$P_W^{r,y,t} = \begin{cases} 0 & V_s^{r,y,t} \leq V_s^{ci} \\ f\left(V_s^{r,y,t}\right) & V_s^{ci} \leq V_s^{r,y,t} \leq V_s^{r} \\ P_W^{\max} & V_s^{r} \leq V_s^{r,y,t} \leq V_s^{co} \\ 0 & V_s^{r,y,t} \geq V_s^{co} \end{cases} \quad \forall r\in R, y\in Y, t\in T \tag{8}$$

4. Test system and input data

The proposed model is simulated on the building shown in Fig. 2. The building is powered by electrical grid and wind turbine (Hemmati, 2017). The rated power of wind turbine is 100 kW and the peak load is 150 kW (Hemmati and Saboori, 2017). The building is also incorporated with energy management tool, uncertainty, and multiple time scale modelling (Hemmati and Saboori, 2017).

The seasonal profiles for load power and wind energy are considered as listed in Table 1 (Hemmati, 2017; Mehrjerdi, 2019d). Daily profiles for load and wind powers are also listed in Table 2 (Hemmati, 2017; Mehrjerdi et al., 2019). Three different time scales are modeled for wind and load profiles including 15, 30, and 60-min Table 3 also shows the time of electricity pricing scheme (Kamyab and Bahrami, 2016).

Uncertainty of wind power is modeled by Weibull distribution and load uncertainty is modeled by Gaussian distribution (Soulouknga et al., 2018). A large set of scenarios is generated by sampling from the uncertain parameters and model is expressed as stochastic programming.

5. Simulation results and discussions

The proposed multiple time-scale model is simulated on the introduced test system. Table 4 shows the annualized cost under multiple time-scale model. The results demonstrate that considering shorter time scale provides more accurate outputs. Furthermore, reducing the time-scale from 60 to 30-min, the cost will be reduced about 5% and the time-scale from 30 to 15-min and cost about 3%. The shorter time scales allow the model to operate under flexible condition resulting in more accurate and reasonable outputs.

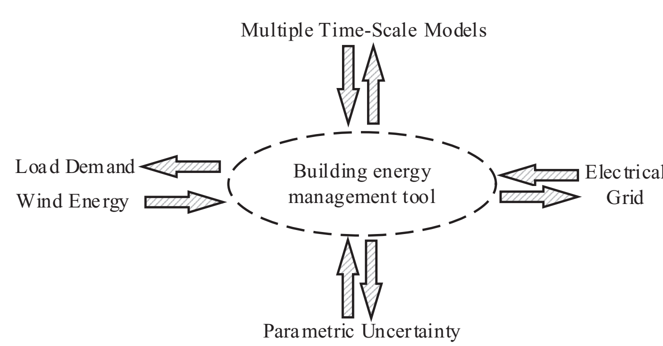

Fig. 2. Building powered by wind-grid under uncertainty and multiple time-scale model.

Table 1
Seasonal profile for load power and wind energy.

	Season 1	Season 2	Season 3	Season 4
Loading and wind energy (%)	100	125	90	80

The traded power between the building and network is optimized under multiple time-scale models and depicted through Figs. 3–5. The power between the building and network under 15-min time scale model is depicted in Fig. 3. The building sends excess of its energy to the grid at time intervals 0 to 35 and 85 to 96 when the energy demand is not much. On the other hand, the building receives the energy from the grid at time intervals 36 to 84 when the energy demand is high. The 15-min time-scale allows the

Table 2
Daily profiles for load power and wind energy.

Hour	60 min wind profile (%)	30 min wind profile (%)	15 min wind profile (%)	60 min load profile (%)	30 min load profile (%)	15 min load profile (%)	Hour	60 min wind profile (%)	30 min wind profile (%)	15 min wind profile (%)	60 min load profile (%)	30 min load profile (%)	15 min load profile (%)
1	0.8	0.8	0.8	0.15	0.15	0.15	49	0.5	0.5	0.5	0.85	0.85	0.85
2	0.8	0.8	0.81	0.15	0.15	0.13	50	0.5	0.5	0.48	0.85	0.85	0.84
3	0.8	0.83	0.83	0.15	0.12	0.12	51	0.5	0.47	0.47	0.85	0.83	0.83
4	0.8	0.83	0.84	0.15	0.12	0.11	52	0.5	0.47	0.46	0.85	0.83	0.81
5	0.85	0.85	0.85	0.1	0.1	0.1	53	0.45	0.45	0.45	0.8	0.8	0.8
6	0.85	0.85	0.86	0.1	0.1	0.09	54	0.45	0.45	0.43	0.8	0.8	0.79
7	0.85	0.87	0.87	0.1	0.1	0.08	55	0.45	0.4	0.4	0.8	0.78	0.78
8	0.85	0.87	0.88	0.1	0.1	0.07	56	0.45	0.4	0.37	0.8	0.78	0.76
9	0.9	0.9	0.9	0.1	0.08	0.06	57	0.35	0.35	0.35	0.75	0.75	0.75
10	0.9	0.9	0.91	0.1	0.08	0.05	58	0.35	0.35	0.36	0.75	0.75	0.7
11	0.9	0.92	0.92	0.1	0.08	0.05	59	0.35	0.37	0.37	0.75	0.65	0.65
12	0.9	0.92	0.93	0.1	0.08	0.06	60	0.35	0.37	0.38	0.75	0.65	0.62
13	0.95	0.95	0.95	0.05	0.05	0.06	61	0.4	0.4	0.4	0.6	0.6	0.6
14	0.95	0.95	0.96	0.05	0.05	0.07	62	0.4	0.4	0.41	0.6	0.6	0.62
15	0.95	0.93	0.93	0.05	0.07	0.06	63	0.4	0.42	0.42	0.6	0.65	0.65
16	0.95	0.93	0.91	0.05	0.07	0.07	64	0.4	0.42	0.44	0.6	0.65	0.67
17	0.9	0.9	0.9	0.1	0.1	0.1	65	0.45	0.45	0.45	0.7	0.7	0.7
18	0.9	0.9	0.88	0.1	0.1	0.11	66	0.45	0.45	0.46	0.7	0.7	0.71
19	0.9	0.87	0.87	0.1	0.12	0.12	67	0.45	0.5	0.5	0.7	0.72	0.72
20	0.9	0.87	0.86	0.1	0.12	0.13	68	0.45	0.5	0.53	0.7	0.72	0.73
21	0.85	0.85	0.85	0.15	0.15	0.15	69	0.55	0.55	0.55	0.75	0.75	0.75
22	0.85	0.85	0.83	0.15	0.15	0.16	70	0.55	0.55	0.58	0.75	0.75	0.8
23	0.85	0.82	0.82	0.15	0.17	0.17	71	0.55	0.6	0.6	0.75	0.85	0.85
24	0.85	0.82	0.81	0.15	0.17	0.18	72	0.55	0.6	0.63	0.75	0.85	0.9
25	0.8	0.8	0.8	0.2	0.2	0.2	73	0.65	0.65	0.65	1	1	1
26	0.8	0.8	0.78	0.2	0.2	0.21	74	0.65	0.65	0.68	1	1	0.99
27	0.8	0.77	0.77	0.2	0.23	0.23	75	0.65	0.7	0.7	1	1	0.98
28	0.8	0.77	0.76	0.2	0.23	0.24	76	0.65	0.7	0.73	1	1	0.98
29	0.75	0.75	0.75	0.25	0.25	0.25	77	0.75	0.75	0.75	1	0.97	0.97
30	0.75	0.75	0.73	0.25	0.25	0.26	78	0.75	0.75	0.78	1	0.97	0.96
31	0.75	0.72	0.72	0.25	0.3	0.3	79	0.75	0.8	0.8	1	0.97	0.95
32	0.75	0.72	0.71	0.25	0.3	0.32	80	0.75	0.8	0.82	1	0.97	0.94
33	0.7	0.7	0.7	0.35	0.35	0.35	81	0.85	0.85	0.85	0.95	0.95	0.95
34	0.7	0.7	0.71	0.35	0.35	0.39	82	0.85	0.85	0.87	0.95	0.95	0.9
35	0.7	0.75	0.75	0.35	0.45	0.45	83	0.85	0.9	0.9	0.95	0.85	0.85
36	0.7	0.75	0.77	0.35	0.45	0.5	84	0.85	0.9	0.95	0.95	0.85	0.8
37	0.8	0.8	0.8	0.55	0.55	0.55	85	1	1	1	0.75	0.75	0.75
38	0.8	0.8	0.78	0.55	0.55	0.57	86	1	1	0.98	0.75	0.75	0.6
39	0.8	0.77	0.77	0.55	0.6	0.6	87	1	0.97	0.97	0.75	0.55	0.55
40	0.8	0.77	0.76	0.55	0.6	0.65	88	1	0.97	0.96	0.75	0.55	0.5
41	0.75	0.75	0.75	0.7	0.7	0.7	89	0.95	0.95	0.95	0.45	0.45	0.45
42	0.75	0.75	0.74	0.7	0.7	0.72	90	0.95	0.95	0.93	0.45	0.45	0.42
43	0.75	0.66	0.66	0.7	0.75	0.75	91	0.95	0.9	0.9	0.45	0.4	0.4
44	0.75	0.66	0.64	0.7	0.75	0.77	92	0.95	0.9	0.88	0.45	0.4	0.32
45	0.6	0.6	0.6	0.8	0.8	0.8	93	0.85	0.85	0.85	0.3	0.3	0.3
46	0.6	0.6	0.58	0.8	0.8	0.81	94	0.85	0.85	0.84	0.3	0.3	0.24
47	0.6	0.55	0.55	0.8	0.82	0.82	95	0.85	0.83	0.83	0.3	0.2	0.2
48	0.6	0.55	0.52	0.8	0.82	0.83	96	0.85	0.83	0.81	0.3	0.2	0.16

Table 3
Time of electricity pricing pattern.

Hour	1 to 7	8 to 16	17 to 22	23 to 24
Electricity price ($/kWh)	0.12	0.20	0.25	12

Table 4
Annualized cost under multiple time-scale models.

Time scale	15 min	30 min	60 min
Annualized cost ($/year)	35734	36988	38106

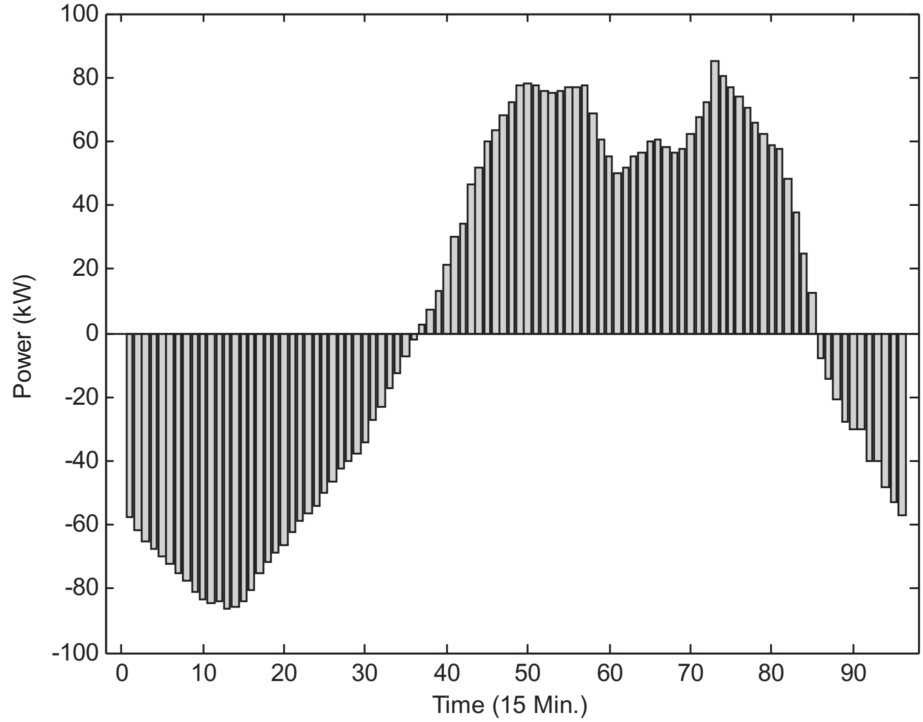

Fig. 3. Traded power between building and network under 15-min time-scale and uncertainty modelling.

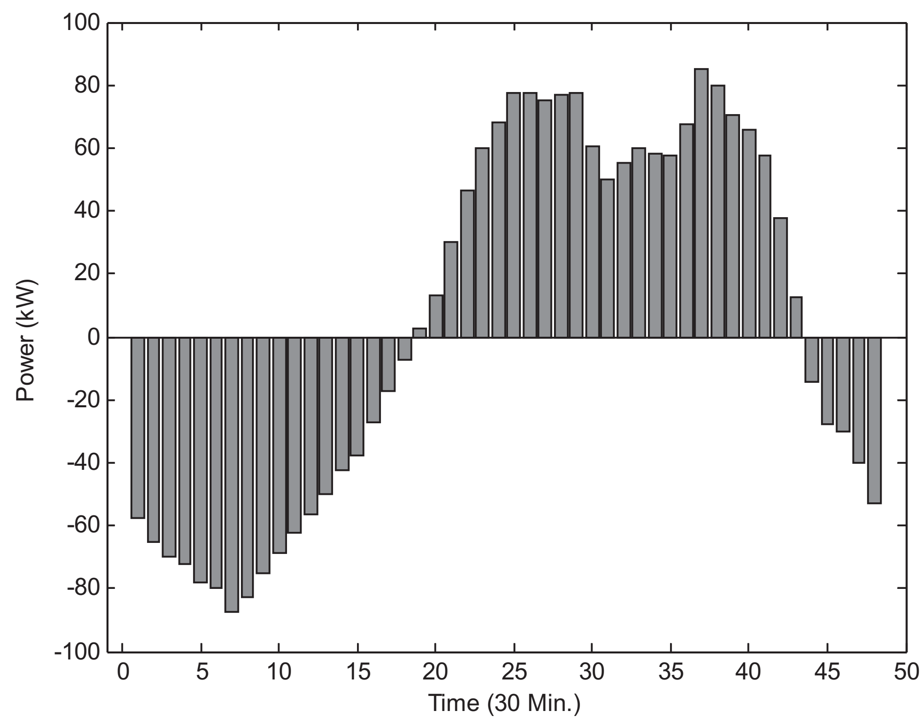

Fig. 4. Power between building and network under 30-min time scale.

building to change its operating condition under every time interval resulting in the optimal performance for building. On-peak loading of the system is seen at time interval 73.

The traded power under 30-min time scale pattern is depicted in Fig. 4. The general schematic of the power profile is similar to Fig. 3. However, the 30-min time scale is less flexible and building cannot efficiently manage the energy. The building trades energy with the grid to balance the energy consumption-generation.

The power under 60-min time scale is given in Fig. 5. The output has 24-h time period. The output is similar to the previous power profiles but comprising less flexibility. The energy management tool is only able to change the power at one-hour time intervals and

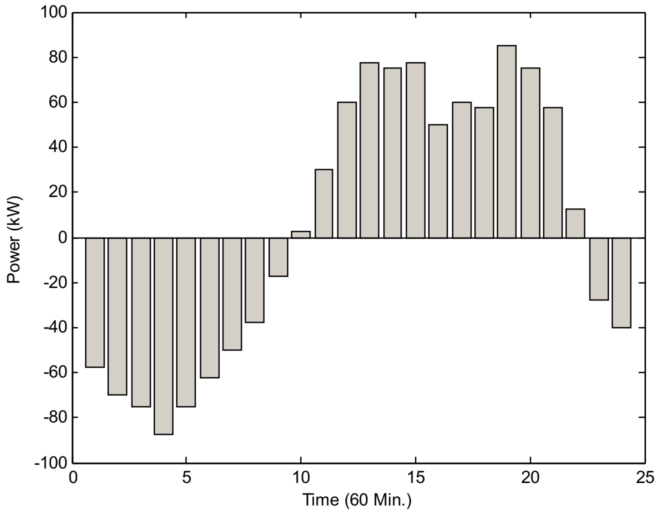

Fig. 5. Power between building and network under 60-min time scale.

Table 5
Seasonal power between building and network under Off-On peak periods.

	Season 1	Season 2	Season 3	Season 4
Time interval 73 (on-peak loading)	85.000	106.250	76.500	68
Time interval 14 (off-peak loading)	−87.500	−109.375	−78.750	−70

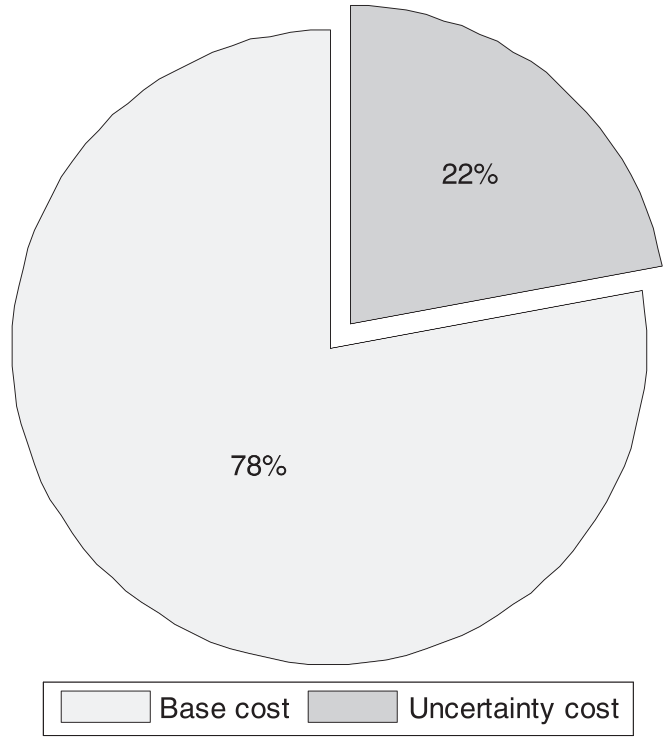

Fig. 6. The level of uncertainty cost in the model.

such long time-interval modelling does not permit the energy management tool to optimize the operation efficiently.

The loads and wind energy are dependent to the seasonal conditions and it is useful to evaluate their operation under seasonal profiles. Table 5 lists the seasonal traded power between the building and network under off-peak time interval (i.e., time period 14) and on-peak time interval (i.e., time period 73). The results specify that the building sends energy to the grid under off-peak time interval and receives energy from the network under on-peak time interval. As well, the traded energy is dependent to the seasons. In season 2, the load is increased under on-peak time interval and the building receives more energy from the grid under on-peak condition. On the other hand, in season 2 the wind energy is increased under off-peak time interval and the building sends more energy to the grid under off-peak period. The highest levels of energy trading are in season 2 and the lowest levels are in season 4.

The proposed model evaluates the impacts and correlation of uncertainty and time-scale at the same time. The uncertainties of the loads and energy similarly make significant impacts on the costs. Fig. 6 presents the level of uncertainty cost in the model. It is verified that the uncertainty of the loads and wind energy increases the plan cost by 22%. The base cost of the plan without uncertainty is 78% of the nominal cost.

The wind power uncertainty is the main source of uncertainty in the proposed stochastic model. In order to demonstrate the impacts of wind power intermittency on the model, several wind power scenarios are defined and simulated as given in Table 6. The outputs verify that reducing the wind power increases the received power from the grid under on-peak loading and decreases the transmitted power to the grid under off-peak loading. The operation is vice versa when wind energy is increased.

Table 7 lists the results for sensitivity analysis on the energy price and loading. It is demonstrated that the loading is the key parameter of the model. Reducing the loading by 10% decreases the annualized cost about 38%. The influence of the energy price on the model is less than the loading. Reducing the energy price by 10% will decrease the annualized cost about 10%.

5.1. Time-scale modeling and simulation time

The shorter time-scales provide more accurate model but they need longer simulation time. As a result, it is required to compromise between the simulation time and accuracy of the model and outputs. In order to address this issue, the simulation time under various time-scale modeling is presented in Table 8. It is clear that the shorter time scale yields longer simulation time and the simulation time is almost unacceptable for very short time scales (330 Minute for 5 min time-scale modelling). The cost is reduced by 5% when the time-scale is reduced from 60-min to 30-min. As a result, the 30-min is more reasonable than 60-min because it increases the accuracy and reduces the cost significantly. However it increases the simulation time by about 100% but its longer simulation time is acceptable because of its substantial influence on the model. In the next item, decreasing the time-scale from 30-min to 15-min decreases the cost by 3%. As a result, the 15-min and its longer simulation time are acceptable because of its significant impact on the model cost and accuracy. The final item reduces the time-scale from 15-min to 5-min that decreases the cost by 0.8% and increases the simulation time by about 300%. The 5-min time scale is not therefore proper because it needs very long simulation time but its improvement on the model cost is not significant. As a result, the optimal time-scale for current test system is 15-min.

It also should be noted that the tradeoff between the simulation time and the model accuracy is mandatory sometimes. Because in the practice, the system operators cannot wait several hours or one day to get the outputs of their models. Some applications are also real-time or short term operations and the operators need to know the outputs after short time periods. As a result, it is useful to study the correlation of time-scale modelling and accuracy of the outputs. The outputs of the introduced test system demonstrate that

Table 6
Sensitivity analysis on wind power uncertainty.

Wind power scenarios	Time interval 73 (on-peak loading)	Time interval 14 (off-peak loading)
Nominal case (wind power by 100%)	85.0	−85.5
Reducing wind power by 10%	91.5	−75.9
Reducing wind power by 20%	98.0	−66.3
Reducing wind power by 30%	104.5	−56.7
Reducing wind power by 80%	137.0	−8.7
Increasing wind power by 10%	78.5	−95.1
Increasing wind power by 15%	75.2	−99.9

Table 7
Sensitivity analysis on energy price and loading.

	Annualized cost ($/year)
Nominal case	142937
Reducing energy price by 10%	128644
Increasing energy price by 10%	157231
Reducing loading by 10%	88130
Increasing loading by 10%	197744

Table 8
The cost under multiple time-scale models.

Time scale	5 min	15 min	30 min	60 min
Simulation time (Minute)	330	108	55	29
Change of cost (%)	0.8%	3%	5%	Base cost

reducing the time-scale period less than 15-min is not required for the given test system because the shorter time-scales do not change the outputs considerably but result in very long simulation times. The proposed methodology can be adapted to the other systems to find optimal time-scale in order to keep both the accuracy and simulation time on the acceptable level.

5.2. Comparing the model

In order to verify the viability of the introduced model, the results of the study are compared with other similar research studies. Table 9 presents the results of comparison study. It is clear that all the models can properly design the energy management system but the proposed model comprises less operational cost. The given model utilizes short time-scale modelling and comprises more flexibility. As a result, it has less operational cost.

6. Conclusions

This paper addressed impacts of time-scale modelling and uncertainty on the operation of RESs and electrical loads. It was demonstrated that the RESs and especially wind energy have short-term variations and their energy profiles are not accurately forecastable. Such error must be modeled and discussed in terms of uncertainty. The proposed technique investigated the correlation of time-scale and uncertainty in energy management systems. Three different time scales including 15, 30, and 60-min were modeled. The uncertainties of the loads and wind energy were also incorporated. The energy management system was modeled on the typical building to optimize the energy consumption. The simulation results demonstrated that the shorter time scale results in more accurate outputs but it comprises longer simulation time. The 30-min time-scale reduces the cost about 5% and 15-min time-scale decreases the cost about 3%. On the other hand, 15-min time-scale takes more simulation time. The building sends excess of energy to the grid at time intervals 0 to 35 and 85 to 96 and receives energy from the grid at time intervals 36 to 84. In season 2, the building receives more energy from the grid under on-peak loading and sends more energy to the grid under off-peak loading. It is also demonstrated that the load-wind uncertainties increase the cost by 22%. Reducing the wind power increases the received power from the grid under on-peak loading and decreases the outgoing power to the grid under off-peak loading. It is also demonstrated that the loading is the key parameter of the model and reducing the loading by 10% decreases the annualized cost about 38%.

Further to this work, it is suggested to consider the other types of RESs in the model, modelling the thermal loads and thermal energies in the building, modelling the electric vehicles and their operation in the building, and considering different probability distribution functions to model uncertainty.

Table 9
Comparing results with other similar research studies.

Time scale	Operational cost ($/year)
The proposed model	35734
The model given by (Hemmati and Saboori, 2017)	37090
The model given by (Hemmati, 2017)	36831

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