An Algorithm for Load Planning of Renewable Powered Machinery with Variable Operation Time

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***Abstract*— This paper presents a multiobjective load planning algorithm for industrial applications with integrated hybrid renewable energy systems (HRES). The focus of the paper is on the planning of loads with time-dependent duration. In some cases, the duration of the machinery operation depends on the external parameters and can vary depending on what time of the day they are operating. The presented algorithm, implemented in the software MOHRES, is based on the multi-criteria assessment of the system against several performance measures. Through a case study, the performance of the algorithm is evaluated. It is shown how the algorithm can successfully find Pareto solutions with minimal production cost and optimal HRES performance measures.**

***Keywords*— HRES, hybrid renewable energy systems, load planning, energy efficient production, MOHRES**

I. Introduction

In industrial applications, load shifting, more known as load planning/scheduling, is established as one the pillars of energy efficiency. Menghi et al [1], in their review paper, argue that manufacturing as the largest end-use sector in terms of both final energy demand and greenhouse gas emissions need to mitigate the environmental impacts of manufacturing processes via implementing energy efficiency. The review paper [2] outline and discuss most of the research reported during the last decade regarding energy efficiency in manufacturing systems. Energy-oriented production planning research is mainly focused on energy-efficient master production scheduling and capacity planning, energy-efficient lot-sizing, as well as energy-efficient machine scheduling [3].

Hybrid renewable energy systems (HRES) are implemented to overcome the challenge imposed by the energy fluctuation where more than one primary energy source, with at least one renewable energy source, are used (e.g. wind-diesel system) [4]. Consequently, HRES have large penetration in power generation due to their capability to meet the electricity demand in a reliable and relatively more environmentally friendly way for both grid-connected and standalone applications [5-7].

While in most of load planning related works (for instance see [8-12]) the load duration is known and fixed and the objective of the load planning is to reduce the emission or minimise the cost of operation, in some cases the actual duration of machinery load is unknown and depends on the external factors. The focus of this paper is on energy efficiency, reducing carbon footprint as well as the production cost while dealing with these types of loads. The next two sections elaborate on how a flexible load with time-dependent duration can be formulated and how a multiobjective optimisation approach can be used to minimise the production cost and maximise the HRES performance measures. It is followed by a section containing a real-world case study showing the performance of the load planning algorithm.

II. Formulation of Flexible Loads with Unknown Duration

Figure 1 shows a typical real-world example of a demand load with flexibility in scheduling while the duration is also unknown and dependent on the timing. Here, a water maker of P_{nom} is used to produce drinking water for a camp. The water maker is required to operate sufficiently to produce a targeted amount of water per day $W_{d,target}(lit/day)$. Here, the duration of the operation for producing the required water is unknown. The production depends on the ambient temperature and the relative humidity, which vary throughout the day, hence the duration can vary depending on the time of operation. In the rest of this section, without loss of generality, we use this flexible load examples to explain the flexible load formulation.

Using hourly averaged data and keeping in mind that the scheduling window is 24 hours, we divide the operation to 24 separate 1-hour operations, all with fixed times t_1 through t_{24} which are known. At each time t_j ($j = 1,2, \dots ,24$), the machine can be off: $L_j = 0$ or on: $L_j = P_{nom}$, as given in Equations (1) and (2) below:

$$L_j \in \{0, P_{nom}\};\ j = 1,2, \dots ,24 \quad (1)$$

$$t_1 = 1;\ t_j = t_{j-1} + 1;\ j = 2, \dots ,24 \quad (2)$$

III. Optimisation Problem Formulation

Normally, when dealing with load planning problems in HRES, we take the advantage of the flexibility in the demand load to plan it in such a way to optimise the performance of the system via:

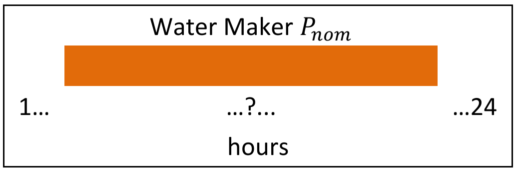

Fig. 1. Example of a flexible load: water maker with unknown operation time to deliver a certain amount of production

- Reducing the unmet load P_u or equivalently, improving the reliability of the system if the HRES is standalone, or decreasing the dependency on the grid in case of on-grid HRES
- Increasing the excess power, P_{ex}, to increase the profit of selling electricity to the grid or using it for another purpose, e.g. hydrogen production
- Where applicable, increasing the battery life index LI_{bat}, and improving the performance of the battery bank in long run. This can be achieved by decreasing the depth of discharge and/or reducing the number of charge/discharge cycles and hence increasing the system lifespan and the replacement cost.
- Increasing the stored energy at the end of the period, for instance, the state of charge of the battery bank at the end of the day, SOC_{24}.
- Decreasing CO_2 emission in a HRES with diesel generator as backup or auxiliary power system.

In systems that deal with production we can also improve the performance by:

- Increasing the production, p where applicable (i.e. HRES-powered systems that operate to produce a targeted production)
- Decreasing the production cost, C_p where applicable

In view of the above the vector of performance measures becomes:

$$\vec{Y} = \{P_u, P_{ex}, LI_{bat}, SOC_{24}, CO_2, p, C_p\} \quad (3)$$

In the context of multiobjective constrained optimisation problem formulation, each one of these performance measures can be treated as an objective to be minimised/maximised or as a constraint:

$$min/\max \vec{Y}_{\mathrm{O}}(L_j) \quad (4)$$

$$s.t.$$

$$\vec{Y}_{\mathrm{C},l} \leq \vec{Y}_{\mathrm{C}} \leq \vec{Y}_{\mathrm{C},u} \quad (5)$$

In the above optimisation problem, $\vec{Y}_O$ is a subset of $\vec{Y}$ and stands for the objectives which have been selected to be optimised through an multiobjective optimisation process:

$$\vec{Y}_{\mathrm{O}} \subseteq \{P_u, P_{ex}, LI_{bat}, SOC_{24}, CO_2, p, C_p\} \quad (6)$$

and $\vec{Y}_{\mathrm{C}}$ is a subset of $\vec{Y} - \vec{Y}_{\mathrm{O}}$ which stands for the constraints.

The performance measures for a generic hybrid wind-PV-battery-fuel cell/electrolyser-diesel configuration are given by Equations 7 to 19. These equations are implemented in MOHRES and reported in [13-16].

The unmet load is the amount of demand load that is not being supplied by the HRES. The hourly averaged unmet load P_u is defined as:

$$P_u = \begin{cases} L - P_a & if \;\; L > P_a \\ 0 & if \;\; L \leq P_a \end{cases} \quad (7)$$

where, L is the hourly averaged demand load and P_a is the hourly averaged available power from renewable, storage and backup components. For a generic wind-PV-battery-fuel cell-diesel configuration, P_a is given by:

$$P_a = P_{WT} + P_{PV} + P_{B,e} + P_{FC,e} + P_{D,nom} \quad (8)$$

in which, $P_{D,nom}$ is the nominal power of the diesel generator, and the rest of the terms on the right hand side of the equation are given as follows.

The power produced by a wind turbine P_{WT} is given by:

$$P_{WT} = \frac{1}{2}\pi\rho {V_{hub}}^3 R_{WT}^2 C_p \eta_{EG} \quad (9)$$

where, V_{hub} is the wind speed at the hub height, R_{WT} is the rotor radius, C_p is the rotor power coefficient, and η_{EG} is the overall efficiency of the mechanical and electrical components of wind turbine.

The power produced by the PV panels P_{PV} is given by:

$$P_{PV} = IA_{PV}\eta_{PV} \quad (10)$$

where, I is the hourly averaged solar irradiance in W/m^2, A_{PV} is the total area of the solar panels, and η_{PV} is the overall efficiency of the of the PV panels.

For a battery bank with n_B batteries of each c_B (Ah) nominal capacity, current state of charge of SOC, and discharging efficiency of η_B, the extractable power from the battery bank $P_{B,e}$ is given by:

$$P_{B,e} = (SOC - SOC_{min}) n_B c_B V_B \eta_B \quad (11)$$

The extractable power from a fuel cell over a period of one hour, $P_{FC,e}$ depends on its nominal power $P_{FC,nom}$ and the extractable mass of hydrogen from the hydrogen tank:

$$P_{FC,e} = min\{P_{FC,nom}, M_{H_2,e} m_{H_2} LHV \eta_{FC}\} \quad (12)$$

where, $m_{H_2} = 2.016 \times 10^{-3}\ kg/mol$ is the molar mass of hydrogen, $LHV = 33000$ Wh/kg is the lower heating value of hydrogen, and η_{FC} is the fuel cell efficiency. The extractable mass of hydrogen from hydrogen tank $M_{H_2,e}$ is given by:

$$M_{H_2,e} = M_{H_2} - M_{H_2,min} \quad (13)$$

in which, M_{H_2} is the mass of stored hydrogen in the tank at the beginning of the one hour period and $M_{H_2,min}$ is the mass of hydrogen unextractable from the tank due to drop in the tank pressure.

The excess power P_{ex} is given by:

$$P_{ex} = \begin{cases} P_{WT} + P_{PV} - L - P_{B,c} - P_{EL,c} \\ \qquad if \;\; P_{WT} + P_{PV} - L > P_{B,c} + P_{EL,c} \\ 0 \qquad otherwise \end{cases} \quad (14)$$

where, $P_{B,c}$ is the required charging power to reach the state of charge of battery to 100%, and $P_{EL,c}$ is the electrolyser power required to fill the hydrogen tank. $P_{B,c}$ is given by:

$$P_{B,c} = \frac{(1-SOC)n_B c_B V_B}{\eta_{B,c}} \quad (15)$$

where, $\eta_{B,c}$ is the battery's charging efficiency, and $P_{EL,c}$ is given by:

$$P_{EL,c} = min\left\{P_{EL,nom}, \left(M_{H_2,max} - M_{H_2}\right)\frac{m_{H_2}LHV}{\eta_{EL}}\right\} \quad (16)$$

where, $P_{EL,nom}$ is the nominal power of the electrolyser, η_{EL} is the efficiency of the electrolyser, and $M_{H_2,max}$ is the mass of the hydrogen in the tank when the tank is fully charged.

The actual life of batteries is the minimum of the nominal lifespan $N_{nom,B}$ and the equivalent life $N_{eq,B}$ in years. The nominal life of lead-acid batteries is about 4 to 5 years. The equivalent life of the battery is calculated using the number of charge-discharge cycles and the depth of discharge for each cycle:

$$N_{eq,B} = \frac{1}{\sum_{k=1}^{n_d} \frac{1}{[n_{cycle\ to\ fail}]_k}} \quad (17)$$

where, n_d is the number of charge-discharge cycles of the battery bank per year, and $[n_{cycle\ to\ fail}]_k$ is the number of cycles that leads to battery failure depending on the depth of discharges. The number of cycles to failure depends on the type of the battery. For deep-cycle lead acid batteries, the number of cycles to failure is given by [14]:

$$[n_{cycle\ to\ fail}]_k = 540.1DOD_k^{-0.991} \quad (18)$$

Here $LI_{bat} = N_{eq,B}$, assuming that the system operates continuously in identical and repeating loading/renewable resource conditions for comparison purpose.

State of charge of the battery bank at the end of each hour can be calculated based on the SOC at the beginning of that hour and the amount of charge/discharge during that hour, depending on the difference between the renewable power and load $(P_R - L)$. Parameter SOC_{24} therefore can be calculated using the recursive equation below:

$$SOC_{i=24} = SOC_{i-1}(1-\delta) + \frac{(P_R - L)_i}{n_B c_B V_B}\eta_B \quad (19)$$

where, $SOC_1 = 1$ (fully charged batteries at the beginning of the scheduling period), δ is the self-discharge rate, η_B is charge/discharge efficiency, n_B is the number of batteries in the battery bank, and $c_B(Ah)$ and V_B are the battery unit capacity and voltage respectively.

IV. Case Study

The $P_{nom} = 9.6\ kW$ water maker of Section 2 (operating in a camp near Abu Dhabi) is powered by a PV-battery system of $A_{PV} = 350\ m^2$ with a PV efficiency of $\eta_{PV} = 16\%$ and a battery bank of $n_B = 150$ deep cycle $24\ V - 80\ Ah$ lead acid batteries with a minimum permissible depth of discharge of 50%. The water maker is normally in operation 24/7. This water maker produces up to 688 litres of water in a typical day of September. For a typical day of September the ambient temperature, humidity and hourly water production are shown in Figure 2 and the solar irradiance is shown in Figure 3. The solar irradiance is also shown on this figure.

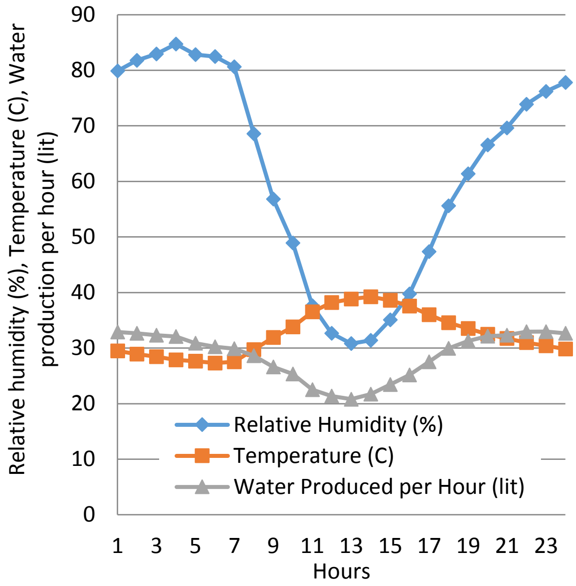

Fig. 2. Ambient temperature, relative humidity and hourly production of water for a typical day of September

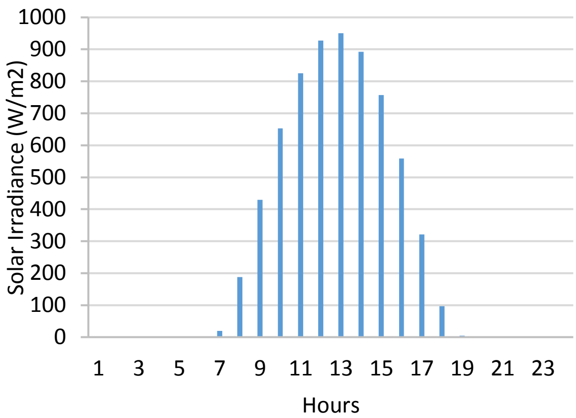

Fig. 3. Solar irradiance for a typical day of September

The production model as a function of the ambient air temperature T(°C) and relative humidity φ(%) is given by:

$$W_h = 0.086(e^{0.0531T})\varphi \quad (20)$$

We want to use this water maker for generating only 350 litre of water due to a change in the number of workers in the camp (change in production target). The lifespan of the water maker, hence the cost of production, depends on the total number of hours of operation. Now the question is what time of the day the water maker should operate to produce the target amount of water while operating the minimum number of hours. Also, we are looking for those solutions in which the water maker is fully powered by renewables without any unmet load ($P_u = 0$), while the state of charge of the battery bank remains above or at least equal to the minimum permissible state of charge ($SOC_j \geq SOC_{min}$). Moreover, ideally, we are looking for solutions in which the battery bank is fully charged at the end of the day, making the system ready for operation at the start of the next day. The general optimisation problem above is therefore converted to the following optimisation problem:

$$min\{C_p\} \text{ and } max \ \{P_{ex}, LI_{bat}\} \quad (21)$$

$$s.t.$$

$$p \geq 350 \ lit \quad (22)$$

$$SOC_{24} = 1 \quad (23)$$

$$P_u = 0 \quad (24)$$

Implementing the optimisation problem above in MOHRES and using its integrated NSGA-II multiobjective optimisation algorithm, 9 Pareto solutions satisfying the constraints above are obtained. These solutions are shown in Figure 4. Figure 5 shows the operation scheduling of these solutions and Table I shows their performance measures.

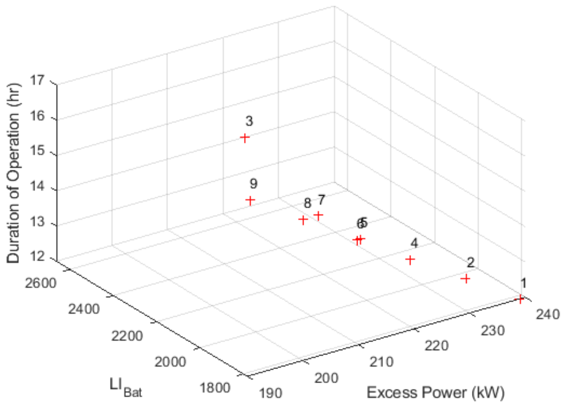

Fig. 4. Pareto solutions of multiobjective optimisation problem (8)

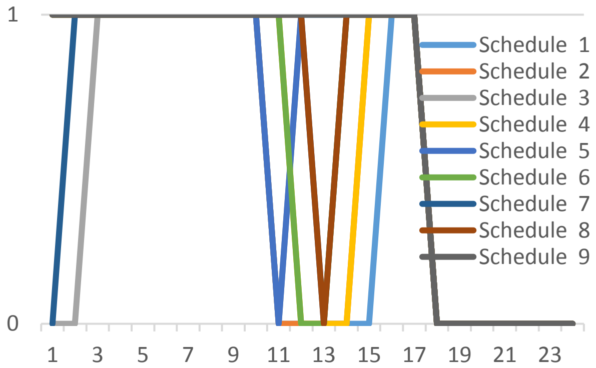

Fig. 5. Load planning Pareto solutions: Schedulling

TABLE I. LOAD PLANNING PARETO SOLUTIONS: PERFORMANCE MEASURES

# Sol	P_{ex} (kW)	$LI_{bat}(day)$	p (lit)	# Hours of Operation $\sim C_p$
1	239	1782	354	12
2	229	1782	378	13
3	224	2663	376	14
4	219	1782	400	14
5	210	1782	421	15
6	210	1782	422	15
7	203	1782	431	16
8	200	1782	443	16
9	191	1782	464	17

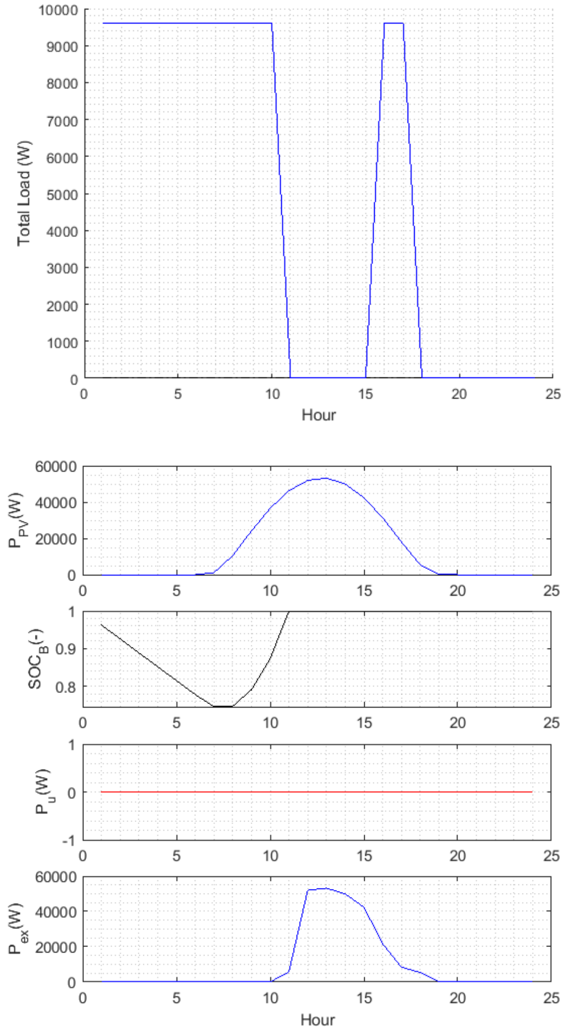

Fig. 6. Solution #1-top: operation scheduling, bottom: 24-hour period power balance

The operation duration of these solutions varies between 12 and 17 hours. Solution #1 with the lowest operation duration of 12 hours has the highest lifespan of the water maker. Moreover, this solution has the highest excess power, which can be turned into an advantage if utilised for supplying other loads such as lighting or cooling. Figure 6 shows the operation scheduling and the 24-hour period power balance of the water maker system with operation scheduling #1. As it can be seen from this figure the system runs on renewables only ($P_u = 0$), the system is ready for operation at the start of the next day ($SOC_{24} = 1$), and the $SOC > SOC_{min}$ by a good margin.

Although operation scheduling #9 is one of the Pareto solutions, one could identify this solution as a good solution even without conducting the optimisation, just by referring to the water production curve in Figure 1 (more water production rates at early hours of the day and charging the battery bank towards the end of the daylight). Taking operation scheduling #9 as the base solution and comparing that to solutions #1, we see a 5 hours reduction in the water maker operation time, which is equivalent to 29% longer lifespan. Comparing solution #9 with solution #3, we observe 49% longer lifespan (LI_{bat}=2663 versus LI_{bat}=1782) for the battery bank.

One may argue that since we are looking for the solution with minimum production cost there is no need for a multiobjective optimisation, and a single objective optimisation will be adequate to deliver the problem at hand. However, by adopting a multiobjective optimisation approach we obtain other nondominated solutions which may be of interest to us. For example, by taking a closer look at the other scheduling scenarios, we see that, for instance, the second-best solution in terms of the production cost (operation scheduling #2) produces about 8% more water than the target value. This can be seen as an advantage for this solution compared to the operation scheduling #1 due to uncertainties in influencing parameters (ambient temperature and humidity) and renewable resources data (solar irradiance). Although all solutions produce enough water satisfying the constraint $p \geq 350\ lit$, solution #9 produces the highest amount of water which can be seen as an advantage if the storage of the water is an option. Operation scheduling #3 is the best solution in terms of the life index of the battery bank leading to longer lifespan for the battery bank and therefore smaller replacement cost.

V. CONCLUSION

There are load-planning problems in which the flexible loads have time-dependent duration due to their dependency on the external parameters. The problem formulation and multiobjective optimisation algorithm presented in this paper allows us to deal with this kind of problems and to find the Pareto solutions with respect to multiple criteria related to the power system performance and the production. The real-life case study presented in this paper shows how the algorithm successfully finds Pareto solutions and why adapting a multiobjective optimisation instead of a single objective one provides us with more options to select from depending on the operating conditions.

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