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Mixed Integer Programming-Based Power Scheduler for the Space Station

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This paper proposes a new mixed integer programming-based optimization model for power scheduling in a space power system. The model has the capability of handling multiple objectives by maximizing the available sources of energy and minimizing the variation of loads over a day. It can also incorporate several complex interactions between the loads in a space system. The modeling framework is illustrated using a simplistic case study for the Space Station Freedom. Detailed results and inputs to the model are presented and several potential enhancements of the model have been summarized.

Nomenclature

$BASE_t$	=	constant base load in t, kWh
B^{max}, B^{min}	=	upper and lower limits on kilowatt-hour output from battery
B_t	=	output from the battery (batteries) in period t, kW
$E_{i,t}$	=	scheduling of loads I in period t, 0 or 1
I	=	set of loads (I = 1, . . . , I), e.g., signal processing, accommodation, etc.
$kWh_{i,t}$	=	kilowatt-hour demand of load I in t
P_{av}	=	average demand in kilowatt-hours for the whole day
S_t	=	forecast of solar output in kilowatt-hours at t
T^0	=	relaxation matrix of equations $h_i(x) = 0$, given by $T^0 = (t_0^{ii}) = [\mathrm{sign}(\lambda_i^0)]$
t	=	time-steps for the schedule, 10-min for the present study
V	=	variance of the total load for the day
W	=	total unused energy, kWh
w^0, w^p	=	weights on the slack variables s^0 and p
α	=	to find the best integer solution in the convex hull determined by the half-spaces at (x^0, y^0)
λ_i^0	=	Lagrangian multipliers of equality constraint I

I. Introduction

THE space power system operates on two sources of energy: 1) photovoltaic blankets and 2) batteries. There can be various types of loads with varying degrees of flexibility of usage and priorities, ranging from regular household needs to supporting life-saving equipment. The objective of a power scheduler in a space station (which may also be referred to as a prescheduler to distinguish its ahead-of-time off-line planning function from the on-line rescheduling function), is to maximize the utilization of the available energy while maintaining the restrictions on the usage of energy to the extent possible. The availability of energy is constrained by the periodicity of solar power and the storage capability of the battery. The space power system design with the combination of photovoltaic blankets and battery ensure adequate supply capacity at all times. The usage of energy is constrained by the degree of flexibility by which certain load can be scheduled in different time periods. The loads can be categorized as interruptible, noninterruptible, restartable, and nonstartable based on their controllability and are treated differently in the scheduling process.

The two classes of problem for utilizing available energy effectively and efficiently are as follows:

1) Off-line power scheduling, which determines the schedule for the next several hours (e.g., 24 h) based on the forecast of load and solar power availability. The off-line study puts relatively less emphasis on the speed requirement for computation and more emphasis on evaluation of the schedule from different criteria, the ability to handle various types of constraints, and the robustness of the schedule to withstand contingencies, etc.

2) On-line power rescheduling is needed in the event of a contingency to optimally reschedule the loads to minimize the unused energy while keeping priority on certain types of loads and minimum disturbance of the original optimal schedule determined in the off-line study. The computational performance of the on-line rescheduler is an important criterion and may play a critical role in selection of the appropriate tools to enable fast response under contingency conditions.

A. Overview of the Space Power Scheduling Literature

Ringer and Quinn[1] have developed a scheduler for the Space Station test bed that employs a depth-first search to place as many loads as possible in a short amount of time. The shortcoming of this strategy is that it does not ensure optimality. A rule-based approach has been adopted by Bouzguenda and Rahman[2] to minimize unused energy in the rescheduling process. A value-driven scheduling algorithm based on the dynamic programming approach, which assigns costs to each subtask and perform optimization to remove all unprofitable tasks, has been used by Krupt.[3] Barton[4] outlines several important objectives for load scheduling, for example, maximum vehicle utilization, even distribution of load, flexible operator control, and prioritized load processing, etc. Extensive applications of various optimization schemes have been tested by Sheskin.[5–7] A small scheduling program was developed[5] for a 10-period optimization using a simplistic zero–one integer

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programming code. This research was further extended[6] with battery charging adequately modeled and using the zero–one optimization method (ZOOM). However, the scheduling phenomenon was still devoid of many of the real-life complexities. The Lagrangian relaxation (LR) algorithm has been used for solving the mixed-integer programming scheduling formulation.[7] The motivating factor for employing LR is to generate an upper bound on the optimal value of the objective function. LR also has the flexibility of modeling soft constraints, i.e., the scheduling constraints that can be violated for a price. However, the limitations of the LR algorithms are well known and have been encountered even for small-scale problems. Of the two LR schemes used,[7] the first one failed to produce any solution, and the other oscillated between two solutions. Momoh and Al Basheer[8] describe an expert system-based optimization process for the efficient rescheduling of load.

B. Space Station Freedom Power System

The Space Station Freedom (SSF) is a joint venture project between the U.S. and several other countries. The space station will comprise three laboratories with a capacity of 10–24 international standard payload racks, the Canadian mobile serving system, and a habitation module. The present study has been carried out using a simplified power management and distribution system (PMAD) test-bed for Space Station Freedom as described in Fig. 1. The station will be powered by six solar array wings. Each wing is 112 ft long and 39 ft wide to accommodate 32,800 solar cells that will generate 18.75 kW of power. The total power demand for the station is 56.25 kW, of which 26.25 kW is allocated for housekeeping usage. Since the station will be orbiting around the Earth in 92 min, with an approximate altitude of 208–285 statute miles, and an inclination of 28.5 deg to the equator, it will have an approximate eclipse time of 36 min. The battery storage system is expected to provide energy at the eclipse time. Other supplementing power equipment is needed to transfer the energy from solar arrays and batteries to the payloads and other systems. This equipment includes 1) sequential shunting units (SSU) acting as power regulators, 2) main bus switching units (MBSU) for converting dc voltage from 160 to 120 V, 3) dc/dc converter units (DDCU) acting as regulators, and 4) secondary and tertiary power distribution assembly (SPDA and TPDA) to distribute power to the payloads. A detailed description of all the PMAD subsystems can be found in Ref. 9 and is beyond the scope of this paper.

The following assumptions are made in the present scheduling study to keep the computational burden within a practicable limit:

1) The spatial location of the payloads is not considered.

2) The electrical characteristics of the network are not represented.

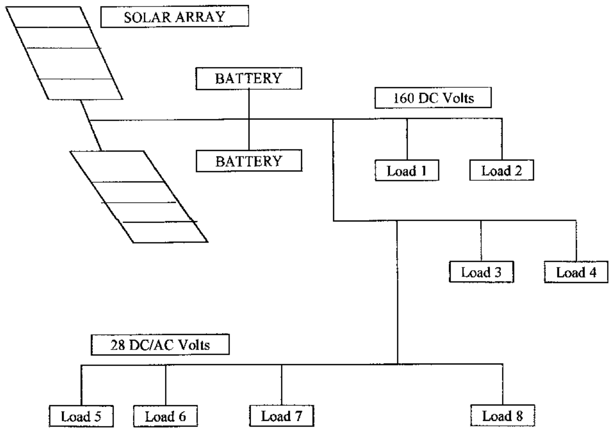

Fig. 1 Simplified presentation for the Space Station Freedom power system.

3) The power losses in the battery and network are ignored.

4) The scheduling process is considered to be deterministic without taking into account the various sources of uncertainty, for example, contingency situations.

5) Although the charging and discharging phenomenon for the battery is modeled, the long-term planning considerations, like battery life, etc., are not taken into account.

Assumptions 1–4 could be relaxed if the present modeling framework could be enhanced to include the probabilistic dc-load flow analysis. However, it would lead to a significant increase in the computational requirements. Efficient algorithms that take advantage of the temporal separability of the dc-load flows across different time-steps are currently being investigated for this purpose. The present exercise, though subject to a number of simplifying assumptions mentioned previously, forms an important step toward developing a comprehensive modeling framework incorporating dc-load flow.

In the present study, an optimization modeling framework has been developed and tested for the off-line power scheduling operation using the simplified PMAD test-bed configuration shown in Fig. 1 and the test data obtained from a previous study.[8] The optimization framework is based on a multiobjective mixed-integer programming framework and is capable of capturing interactions among the loads, and also ensures optimality.

II. Modeling Framework

A. Selection of Tools

The power-scheduling problem for the space power system is comparable to the unit commitment studies conducted for a terrestrial power system; however, there exists some fundamental difference in the system configuration as well as the nature and magnitude of the problem. Unlike the unit commitment study, the prime motivating factor is not the system economics, but the maximum utilization of the available energy and reliable system operations. The system size can be much smaller than a typical terrestrial system. Various optimization techniques have been successfully implemented for unit commitment for electric utilities, for example, linear programming (LP), dynamic programming (DP), linear mixed-integer programming (MP), and nonlinear mixed-integer programming (MINLP) including several efficient large system optimization techniques like Bender's decomposition, Lagrangian relaxation, and augmented Lagrangian relaxation, etc. More recently there has been experimentation with artificial intelligence (AI) techniques like artificial neural network (ANN), expert systems (ES), and genetic algorithms (GA) to get around the computational problems of solving a very large-scale MINLP problem. It is, however, too early to comment on the superiority of any one technique over the others, given the nascent stage of the AI applications.

A mixed-integer programming-based scheduling operation (linear and nonlinear) is formulated in this study. There are several well-known advantages in favor of this formulation primarily because of the ability of handling discrete nature of the variables, e.g., on/off decision. The following are some of the reasons for choosing an MIP-based optimization framework for the present problem:

1) The small system size of a space power system and relatively lower emphasis on computational speed requirements; an optimization framework seems to be quite well-suited for the power scheduling problem.

2) Direct handling of the constraints on mutual interaction among the loads avoids use of complicated and multiple rules used in a rule-based decision making system. Also, the MIP framework can be utilized to analyze the tradeoff among conflicting objectives for explicit evaluation of the schedule in terms of different objectives.

3) The computer implementation of the optimization framework can easily be made, exploiting some of the efficient com-

mercial codes for MIP and MINLP problems like XA/DICOPT/OSL/ZOOM, etc.[10]

4) Enhancing the basic model by gradually adding complexities such as multiobjective analysis, dc power-flow analysis, etc., is a possibility.

B. Model Formulation

The decision-making framework for the next 24 h is divided into equal time-steps of 10-min durations, i.e., $t = 1, \ldots, 144$. The problem can be stated as minimization of the total unused energy (or, maximization of the use of available energy) subject to meeting all of the kilowatt and kilowatt-hour demands, constraints on the output from the battery, constraints on the interaction of loads, and limit on the variance of loads from the average load for the 24-h period.

The decision variables for the model are listed in the Nomenclature.

The objective function could be either W or V, or the combination of the two. W and V are defined as the following:

$$W = \sum_t (S_t + B_t) - \sum_{i,t} E_{i,t} \cdot \mathrm{kWh}_{i,t} - \sum_t \mathrm{BASE}_t \tag{1}$$

$$V = \sum_t \left(\sum_i E_{i,t} \cdot \mathrm{kWh}_{i,t} + \mathrm{BASE}_t - P_{\mathrm{av}} \right)^2 \tag{2}$$

Note that S, kWh, and BASE are parameter inputs in the model, whereas P_{av} is a variable determined endogenously, depending on the schedule of the experiments (or loads) $E_{i,t}$.

The constraints include the following:

1) *Load and energy balance*: The total available energy from the solar source and battery must be higher than the total demand from all experiments:

$$S_t + B_t \geq \sum_i E_{i,t} + \mathrm{BASE}_t \tag{3}$$

2) *Limits on the battery output*: There are upper and lower limits on the output from the battery, depending on the maximum and minimum discharge rates for the battery system:

$$B^{\min} \leq B_t \leq B^{\max} \tag{4}$$

3) *Sequencing of load*: There can be a particular sequence of occurrence of a specific set of experiments, for example, experiment X must precede experiment Y by N time-steps:

$$E_{X,t-N} = E_{Y,t} \tag{5}$$

4) *Simultaneous occurrence of loads*: There may be two experiments that must be conducted simultaneously, for example, experiments X and Y must occur at the same period:

$$E_{X,t} = E_{Y,t} \tag{6}$$

5) *Exclusivity of loads*: Certain experiments may not be conducted together, i.e., their occurrence must be mutually exclusive, for example, experiments X and Y must not occur together in the same period:

$$E_{X,t} + E_{Y,t} = 1 \tag{7}$$

6) *Limits on the load variance*: One way of limiting excessive variation of the load from one time-step to the other would be to put an upper limit on the variable V, instead of treating it as an objective function:

$$V \leq V^{\max} \tag{8}$$

C. Computational Aspects

The optimization problem described in Sec. II.B is a quadratic mixed-integer programming problem. The variance equation [Eq. (2)] is the only source of nonlinearity. Because of the nonlinearity as well as the large number of binary variables $t \times I$ ($t = 144$, number of time-steps in a day and $I = 8$, number of loads), the standard zero–one optimization technique[11] is not suited for the present problem. Solving a large-scale MIP involves evaluating the objective function at various possible combinations of the binary variables (also referred to as nodes in the terminology of integer programming methods). However, because of the large number of combinations to be evaluated, different efficient Branch and Bound techniques (B&B) are used, which essentially solve a series of relaxed linear programming problems and check for the optimality of the solution at each integer configuration. The efficiency of the MIP algorithm basically depends on the branching scheme. A fixed-order branching is the simplest among all B&B procedures. The more sophisticated B&B procedures utilize better information at each intermediate solution step to decide on the next combination of integer variables. There are commercial solvers available that employ highly efficient versions of B&B schemes. For the present problem, the general algebraic modeling system, a high level language for writing optimization codes, has been utilized. The discrete and continuous optimizer (DICOPT) has been used for solving the nonlinear MIP problem. The DICOPT algorithm[12,13] employs an efficient decomposition scheme called the outer approximation (OA) method. The OA method breaks the solution of the overall problem into the iterative solution of a linear MIP (master problem) and a continuous nonlinear subproblem. The master and the subproblem are solved iteratively by fixing the integer variables in the subproblem and linearizing the nonlinear constraints to the master problem. The iteration between the two subproblems is referred to as the major iteration. The basic idea in DICOPT is to add more and more information about the nonlinear constraints to the linear master MIP with each major iteration. The master problem provides an upper bound to the (minimization) problem, whereas the nonlinear subproblem provides a nonincreasing sequence of lower-bounds to the original problem. The search stops when the subproblem starts worsening, i.e., it gives an objective function value that is higher than that of the last iteration.

We provide a mathematical description of the solution procedure. The MINLP problem can be described as

$$\text{Minimize} \quad Z = C'y + f(x) \tag{9}$$

$$s.t. \quad h(x) = 0 \tag{10}$$

$$Dx \leq d \tag{11}$$

$$By + Cx \leq b \tag{12}$$

where

y	=	represents the binary decision variables like placing a load in a specific time period
x	=	represents the continuous variables like battery discharge
Eq. (9)	=	objective function viz. minimum wastage of energy, or variation of load
Eq. (10)	=	represents the equality restrictions
Eq. (11)	=	stands for all the upper and lower limits on the continuous variables viz. discharge limits
Eq. (12)	=	relates the x and y variables in the form of demand–supply balance

Let k be the index of major iterations between MIP and nonlinear programming (NLP). The detailed steps are described next:

Table 1 Summary of the controllable loads

Experiment	Description	Kilowatt demand	Priority	Duration
1	Radio frequency system	3.07	3	51
2	Antenna	0.89	5	75
3	Audio	0.78	7	80
4	Signal processing	1.46	6	86
5	Data management	2.68	8	66
6	Accommodation	5.97	1	32
7	Root mean square	2.77	4	43
8	Health maintenance	3.82	2	33
Total	Controllable loads	21.44	——	——

Note: Demand is assumed to be constant for the duration.

Step 1: Solve the relaxed NLP problem by allowing the binary variables to assume continuous values between 0 and 1. Let the solution be (x^0, y^0). If y^0 is the integer, STOP, or else, set $z^1 = \infty$, and go to step 2.

Step 2: Set up the master MIP to get y^{k+1}:

$$Z^k = \text{MIN } C'y + \alpha + \sum_k w_k^0 \cdot s_k^0 + \sum_{i,k} w_{ik}^p \cdot p_{ik} \quad (13)$$

$$s.t. \quad f(x^k) + \Delta f(x^k)'(x - x^k) - \alpha \le s_k^0(s \ge 0) \quad (14)$$

$$T_k^0[h(x^k) + \Delta h(x^k)(x - x^k)] \le p^k(p \ge 0) \quad (15)$$

$$\sum_{i \in B_k} y_i - \sum_{i \in N_k} y_i \le |B_k| - 1 \quad (16)$$

$$Dx \le d \quad (17)$$

$$By + Cx \le b \quad (18)$$

There are three basic concepts involved in this solution process:

1) Adding penalty parameters in the objective function for violation of constraints: DICOPT circumvents the problem of nonconvexity of the functions $f(x)$, $g(x)$, and $h(x)$ by adding slack variables on the right-hand side of all the inequality constraints and adding these slacks with a suitable selected weight in the objective function. The weights are selected sufficiently higher than the Lagrangian multipliers associated with these constraints. The augmented penalty ensures that the global optimal point is not cut off from the search space by artificially inflating the search space using slack variables.

2) Relaxation of equality constraints to form inequalities: the property exploited to relax the equality constraints (10) in the form of Eq. (15) exploits the convexity property of the nonlinear function added to the assumption that under certain assumptions, an equality constraint has an equivalent inequality representation.

3) Integer cuts to avoid repetition of the same load allocation schedule entering the solution: Eq. (16) ensures that the same integer solution, i.e., the load allocation schedule, does not enter the subsequent iterations.

Step 3: Solve the NLP subproblem to get (x^{k+1}, y^{k+1}) with objective z^{k+1}. Set $z^{\text{new}} = z^{k+1}$.

Step 4: If $z^{\text{new}} \ge z^{\text{old}}$, STOP. If $z^{\text{new}} \le z^{\text{old}}$, set $z^{\text{old}} = z^{\text{new}}$, and return to step 2, i.e., the master MIP.

The solution process starts by solving the NLP in which the binary variables are relaxed, i.e., binary variables can take up any value between 0 and 1. If the solution itself is an integer, the search stops, otherwise it continues with an iterative process between the NLP subproblem and the master MIP. The NLP problem is solved at each major iteration given a fixed set of binary variables from the master MIP. The NLP subproblem provides a lower bound on the objective function, whereas the master problem provides an upper bound. These upper bounds decrease monotonically because new linearizations are being accumulated at each iteration. The last step is essentially a heuristic relying on the augmented penalty to check for the worsening of the NLP subproblems. Remarkable success of the DICOPT algorithm has been reported[14] for solving highly complex chemical process engineering problems.

Table 2 Summary of power sources and loads

Parameter	Design value
Controllable load	21.44 kW
BASE_t	81.48 kW
Solar cell efficiency	12.00%
Solar array area	820 m^2
Peak PV output	164.5 kW
Peak storage output	104.5 kW
Battery storage	500 A-h
Initial charge	100.00% of full charge
Minimum discharge	40.00% of full charge

Table 3 Insolation levels for the study

Time-step, 10-min intervals	Insolation
$t = 1$	0.00
$t = 2$	721.83
$t = 3$	1443.65
$t = 4$	1443.65
$t = 5$	1443.65
$t = 6$	1443.65
$t = 7$	1443.65
$t = 8$	866.19
$t = 9$	0.00

Note: The insolation follows a cyclical periodicity approximately every nine time-steps, i.e., $t = 10$ has the same level as $t = 1$, $t = 11$ is same as $t = 2$, and etc.

Table 4 Computational steps in the DICOPT algorithm for the VARIAN scenario

Major iteration	Step	CPU time	Iterations
1	NLP subproblem	20.32	480
1	Master MIP	2.07	66
2	NLP subproblem	6.59	145
2	Master MIP	27.11	73
3	NLP subproblem	5.16	145

III. Test Results

A case study for the future SSF was conducted in an earlier rescheduling study.[8] We have used the database of the case study,[8] which is included in Tables 1–3.

Three scenarios are created:

Table 5 Comparison of the scenarios

Scenario	W, kWh	V, kW^2	Total energy for the day, kWh
WASTE	1859.0	440.8	3920.5
VARIAN	1893.1	313.1	3954.5
SEQUEN	1860.4	491.1	3921.7

1) WASTE: minimize the total energy wasted without any limit on variance and without taking into account the sequencing/inclusivity/exclusivity constraints.

2) VARIAN: minimize the variance of total load without any limit on the total energy wasted and also without taking into account the sequencing/inclusivity/exclusivity constraints.

3) SEQUEN: minimize the total energy wasted without any

Table 6 Scheduling of experiments over time-steps $t = 1, \ldots, 144$

Experiments	WASTE	VARIAN	SEQUEN
1	8, 15, 84, 139, 140, 143	9, 10, 11, 78, 79, 80	12, 13, 14, 42, 44, 83
2	31, 32, 56, 119, 120, 121, 125, 128	1, 4, 62, 71, 72, 109, 125, 133	6, 7, 8, 11, 53, 56, 121, 123
3	12, 20, 21, 58, 59, 84, 96, 128	58, 61, 63, 128, 129, 130, 131	4, 5, 129, 137, 140, 141, 142, 143
4	15, 52, 104, 110, 111, 115, 121, 122, 129	52, 53, 54, 55, 56, 121, 122, 123, 124	13, 33, 35, 38, 119, 122, 129, 137, 139
5	47, 50, 115, 116, 119, 124, 132	46, 47, 48, 49, 115, 116, 117	47, 48, 53, 80, 116, 121, 123
6	40, 41, 53, 110	62, 120, 125, 138	53, 56, 121, 123
7	5, 39, 40, 41, 42	3, 39, 40, 106, 108	15, 39, 119, 123, 133
8	29, 54, 97, 98	2, 28, 31, 102	29, 42, 112, 113

Table 7 Battery output schedules[a]

	Output				Output				Output		
t	WASTE	VARIAN	SEQUEN	t	WASTE	VARIAN	SEQUEN	t	WASTE	VARIAN	SEQUEN
1	0.780	1.000	0.780	49	0.600	0.600	0.600	97	0.600	0.600	0.600
2	0.600	0.600	0.600	50	0.600	0.600	0.600	98	0.600	0.600	0.600
3	0.600	0.600	0.600	51	0.600	0.600	0.600	99	0.780	0.780	0.780
4	0.600	0.600	0.600	52	0.600	0.600	0.600	100	0.780	0.780	0.852
5	0.600	0.600	0.600	53	0.600	0.600	0.600	101	0.600	0.600	0.600
6	0.600	0.600	0.600	54	0.780	0.900	0.780	102	0.600	0.600	0.600
7	0.600	0.600	0.600	55	0.780	0.900	0.780	103	0.600	0.600	0.600
8	0.600	0.600	0.600	56	0.600	0.600	0.600	104	0.600	0.600	0.600
9	0.780	0.930	0.780	57	0.600	0.600	0.600	105	0.600	0.600	0.600
10	0.780	0.930	0.780	58	0.600	0.600	0.600	106	0.600	0.600	0.600
11	0.600	0.600	0.600	59	0.600	0.600	0.600	107	0.600	0.600	0.600
12	0.600	0.600	0.600	60	0.600	0.600	0.600	108	0.780	0.894	0.780
13	0.600	0.600	0.600	61	0.600	0.600	0.600	109	0.780	1.000	0.780
14	0.600	0.600	0.600	62	0.600	0.600	0.600	110	0.600	0.600	0.600
15	0.600	0.600	0.600	63	0.780	0.839	0.780	111	0.600	0.600	0.600
16	0.600	0.600	0.600	64	0.780	0.780	0.780	112	0.600	0.600	0.600
17	0.600	0.600	0.600	65	0.600	0.600	0.600	113	0.600	0.600	0.600
18	0.780	0.780	0.780	66	0.600	0.600	0.600	114	0.600	0.600	0.600
19	0.780	0.780	0.780	67	0.600	0.600	0.600	115	0.600	0.600	0.600
20	0.600	0.600	0.600	68	0.600	0.600	0.600	116	0.600	0.600	0.600
21	0.600	0.600	0.600	69	0.600	0.600	0.600	117	0.780	1.000	0.780
22	0.600	0.600	0.600	70	0.600	0.600	0.600	118	0.780	0.780	0.780
23	0.600	0.600	0.600	71	0.600	0.600	0.600	119	0.600	0.600	0.600
24	0.600	0.600	0.600	72	0.780	0.852	0.780	120	0.600	0.600	0.600
25	0.600	0.600	0.600	73	0.780	0.780	0.780	121	0.600	0.600	0.600
26	0.600	0.600	0.600	74	0.600	0.600	0.600	122	0.600	0.600	0.600
27	0.780	0.780	0.780	75	0.600	0.600	0.600	123	0.600	0.600	0.600
28	0.780	0.900	0.780	76	0.600	0.600	0.600	124	0.600	0.600	0.600
29	0.600	0.600	0.600	77	0.600	0.600	0.600	125	0.600	0.600	0.600
30	0.600	0.600	0.600	78	0.600	0.600	0.600	126	0.780	0.780	0.780
31	0.600	0.600	0.600	79	0.600	0.600	0.600	127	0.780	0.780	0.780
32	0.600	0.600	0.600	80	0.600	0.600	0.600	128	0.600	0.600	0.600
33	0.600	0.600	0.600	81	0.780	0.780	0.780	129	0.600	0.600	0.600
34	0.600	0.600	0.600	82	0.780	0.780	0.780	130	0.600	0.600	0.600
35	0.600	0.600	0.600	83	0.600	0.600	0.600	131	0.600	0.600	0.600
36	0.780	0.780	0.780	84	0.600	0.600	0.600	132	0.600	0.600	0.600
37	0.780	0.780	0.780	85	0.600	0.600	0.600	133	0.600	0.600	0.600
38	0.600	0.600	0.600	86	0.600	0.600	0.600	134	0.600	0.600	0.600
39	0.600	0.600	0.600	87	0.600	0.600	0.600	135	0.780	0.780	0.780
40	0.600	0.600	0.600	88	0.600	0.600	0.600	136	0.780	0.780	0.780
41	0.600	0.600	0.600	89	0.600	0.600	0.600	137	0.600	0.600	0.600
42	0.600	0.600	0.600	90	0.780	0.780	0.780	138	0.600	0.600	0.600
43	0.600	0.600	0.600	91	0.780	0.780	0.780	139	0.600	0.600	0.600
44	0.600	0.600	0.600	92	0.600	0.600	0.600	140	0.600	0.600	0.600
45	0.780	0.780	0.780	93	0.600	0.600	0.600	141	0.600	0.600	0.600
46	0.780	0.949	0.780	94	0.600	0.600	0.600	142	0.600	0.600	0.600
47	0.600	0.600	0.600	95	0.600	0.600	0.600	143	0.600	0.600	0.600
48	0.600	0.600	0.600	96	0.600	0.600	0.600	144	0.780	1.000	0.780

[a]Expressed in fraction of full charge.

limit on variance, but taking into account the sequencing/inclusivity/exclusivity constraints.

The detailed breakdown of the major iterations in the solution process for the VARIAN scenario is presented in Table 4 to demonstrate the computational performance of the DICOPT algorithm.

Note from Table 4 that DICOPT converges in just three major iterations on worsening of the NLP subproblem. The computational time for the scheduling problem on a PC-486 is 61 CPU seconds, 52% of which is spent on solving the NLP and the remaining 48% on MIP problems.

Table 5 represents the broad indicators for comparing the three scenarios.

Note that there is a tradeoff between the load balancing objective and that of minimizing wasted energy. Inclusion of the load interaction-related constraints can cause both of the objectives to deteriorate. In the present case, we have considered very limited interaction among the loads, but in real life there can be much stronger interaction among these loads and identifying the impact of these constraints on the objectives could be much more crucial. The deviation from the minimum waste level or minimum variance can be interpreted as the cost associated with meeting one or more of the following specifications:

1) A particular sequence of experiments to be maintained.

2) Two or more experiments to be performed parallel to each other.

3) Two or more experiments that cannot be performed together.

The significant tradeoff between the two objectives indicate that a proper balance among the two needs to be achieved. For example, a compromise between the VARIAN and WASTE scenario solutions in which the load variation is considerably lower than that of VARIAN, but the energy wastage is slightly higher than that of WASTE, might be more attractive than these two extreme cases. The multicriteria decision making tools like goal programming and compromise programming techniques may be used as a further enhancement of the present scheduling model. The multiobjective programming models jointly optimize multiple objective functions and arrive at the optimal compromise level among the conflicting criteria. Efforts are currently underway to extend the present analysis using compromise programming (CP) technique.[15]

The experiment schedules for the three scenarios are presented in Table 6. The schedule of experiments over the time-steps are indicated in the table, for example, experiment 1 is to be performed in time-steps 8, 15, 84, 139, 140, and 143.

The following major observations are made on the test schedules:

1) Note that the schedules vary significantly when different objectives/constraints are selected in the optimization process.

2) While WASTE and SEQUEN have only three minor constraint differences, the schedules are very different.

3) In general, the minimum variance scenario tends to even out the loads across different time-steps by filling in the valleys, and the WASTE scenario tries to fill as much as possible in the periods of high energy availability. That explains the significant difference between the variance in Table 5.

4) The SEQUEN scenario is a special case of WASTE that tries to accommodate the additional constraints while filling in the experiments in the high-energy availability periods, and thereby further increases the variance.

5) Experiments with relatively higher demand (e.g., experiment 6) are more sensitive to the objective/constraint selection, as evident from the wide variation in the schedules across the three different scenarios.

6) More restrictive conditions, viz., higher degree of interaction among the experiments and noninterruptible experiments, may further increase the load variance vs energy wastage tradeoff.

The B_t for the three scenarios are presented in Table 7. The output is expressed in fraction of the full charge. Note that the battery output schedule, in general, cycles with the solar insolation level over the 90-min period. The three scenarios have differences in terms of cycling the battery because of the different schedule of experiments in different time-steps and the resulting power demand.

IV. Concluding Remarks

This paper discusses an optimization framework for power scheduling function, taking into account the various types of load interactions that might exist between the experiments or loads in a space power station. A case study based on a previous exercise[8] is presented and the results are discussed. We have demonstrated that the schedules may vary significantly, depending upon the criteria under consideration; there exists significant tradeoff among load balancing and minimum waste objectives.

Several enhancements of the basic MIP modeling framework proposed here are currently being investigated, which include the following:

1) Develop a logical framework to identify the constraints on load interactions that should act as input to the model.

2) Incorporate probabilistic considerations like load contingencies, supply equipment failure.

3) Incorporate spatial features like modeling network and relative position of different solar arrays with respect to the experiments using dc-load flow analysis.

4) Perform multiobjective analysis among minimization of energy wastage and load variation objectives using the CP technique.

5) Develop a hybrid expert system-optimization framework for rescheduling based on the scheduler that takes advantage of the MIP framework described herein and the extensions proposed in 1–3, as well as exploiting the strengths of ES for real-time functioning.

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References

[1]Ringer, M., and Quinn, T., "Autonomous Power Expert System (APEX)," *Proceedings of the 25th Intersociety Energy Conversion Engineering Conference* (Reno, NV), 1990.

[2]Bouzguenda, M., and Rahman, S., "Energy Management on Board the Space Station: Rule-Based Approach," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 27, No. 2, 1991.

[3]Krupt, J. C., "An Intelligent Value-Driven Scheduling System for Space Station Freedom with Special Emphasis on the Electric Power System," *Telematics and Informatics*, Vol. 7, 1990.

[4]Barton, J., "Improved Load Scheduling Techniques," *Proceedings of the 23rd Intersociety Energy Conversion Engineering Conference*, 1988.

[5]Sheskin, T. J., "Scheduling Experiments on the Space Station," *Computers Industrial Engineering*, Vol. 14, No. 3, 1988, pp. 315–323.

[6]Sheskin, T. J., "Mixed Integer Program to Schedule Loads and Charge Batteries on Space Station," NASA Summer Faculty Rept., NASA Lewis Research Center, Aug. 1989.

[7]Sheskin, T. J., "An Investigation of Lagrangian Relaxation for Solving a Mixed Integer Programming Formulation of a Space Station Scheduling Model," *Mimeo*, Industrial Engineering Dept., Ohio State Univ., Cleveland, OH, Sept. 1991.

[8]Momoh, J. A., and Al Basheer, O. A., "Power System Management Using Expert Systems with Application to Space Power Systems," *Proceedings of the International Workshop on Power Systems Operation and Planning* (Lagos, Nigeria), 1995, pp. 150–156.

[9]Chiu, S., Chand, and Irving, C., "Knowledge-Based Qualitative Modeling and Adaptive Distribution of Power," *Proceedings of the 25th Intersociety Energy Conversion Engineering Conference* (Reno, NV), 1990.

[10]Brooke, A., Kendrick, D., and Meeraus, A., *GAMS—A User's*

Guide, Boyd and Fraser Publishing Co., 1992.

[11]Singhal, J. A., Mastern, R. E., and Morin, T. L., ''Fixed Order Branch-and-Bound Methods for Mixed-Integer Programming: The ZOOM System,'' Dept. of Management Information Systems, Univ. of Arizona, Tucson, AZ, 1987.

[12]Duran, M. A., and Grossmann, I. E., "An Outer Approximation Algorithm for a Class of Mixed-Integer Non-Linear Programs," *Mathematical Programming*, Vol. 36, 1986, pp. 307–339.

[13]Viswanathan, J., and Grossmann, I. E., "A Combined Penalty Function and Outer Approximation Method for MINLP Optimization," *Computers and Chemical Engineering*, Vol. 14, 1990, pp. 769–782.

[14]Kocis, G. R., and Grossmann, I. E., ''Computational Experience with DICOPT Solving MINLP Problems in Process System Engineering," *Computers and Chemical Engineering*, Vol. 13, 1989, pp. 307–315.

[15]Zeleny, M., *Multiple Criteria Decision Making*, McGraw–Hill, New York, 1982.