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Real-Time Improved Power Management for Autonomous Systems

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Abstract: Power resources on board autonomous systems are limited but power requirements on these systems are increasing due to rapid technology growth. Today's methods for controlling these resources either use expensive and conservative strategies (e.g. reactive control), or employ pre-defined power schedules that heighten the risk of operation failure in a dynamic environment. An intelligent Power Management System (PMS) is required to improve, or maintain, system capability. The strategies proposed in this paper aim to contribute towards an intelligent PMS. Using optimization methods, an adaptive and flexible PMS, capable of constructing the best executable power schedules while satisfying real-time requirements, is presented. A three-level optimization strategy is introduced. Due to the feasibility requirement of the solutions produced, the first level uses a constraint satisfaction approach. Then, the solution is quickly improved using a local search algorithm and, next, a global search algorithm is used in the remaining execution time to explore the possibility of further improvement in the solution. The efficiency of the last two levels is enhanced by use of convex programming techniques. Using a case study, we demonstrate that the proposed PMS is capable of rapidly producing a feasible solution, and subsequently optimizing this solution to provide an improved solution. The proposed PMS is capable of adapting to a dynamic environment, by coping with any change in problem description and problem constraints, and constructing a new best executable solution, while satisfying real-time requirements.

Keywords: Autonomous control, autonomous systems, power management systems, safety-critical systems, optimization.

1. INTRODUCTION

Autonomous systems, such as autonomous vehicles, have become a key area of research. These systems are often deployed to execute tasks which are deemed too dangerous, dull, or dirty for humans to perform. Examples of applications of autonomous systems include remote sensing, surveillance, search and rescue, transportation, and payload delivery (Siciliano and Khatib [2008]). In recent years, the work done in this area has grown significantly, introducing more complex and advanced technologies. As a result, these systems are facing both limited energy resources and increased power demands. Optimal management of available resources is essential to support technological advancements on autonomous systems and to improve overall system capability. Optimal power management is also necessary to achieve reduced operational risks and costs while simultaneously increasing endurance and flexibility.

Today's typical Power Management System (PMS) for autonomous systems regulates the power supply and delivery of the vehicle based on a conservative pre-defined power schedule, or by reactive control, which ensures power is available for the worst-case sustained peak power requirement (Morley and Wall [2010]). This approach is robust in the event of unprecedented changes within an expected range. However, the power inefficiency and equipment costs are high. Additionally, unnecessary pollutant emissions arise as a result of excess power generated. The power inefficiency implies that the operational capability of the system could be extended, if the power usage is improved. Increasingly, longer operation times are a key product feature for autonomous systems. Improved power management is a key enabling technology that offers an efficient way of achieving these requirements (Karunarathne et al. [2011]). Note that power management in this context includes electrical, propulsive, hydraulic, pneumatic, and thermal power.

The system environment, equipment health, and operation objectives are subject to dynamic change throughout operation. These factors increase the potential risk of operation failure. A human controller may communicate an updated power schedule. However, this often requires a significant amount of time and a reliable communication network, both of which are not always available. An update of the power schedules based on real-time dynamical changes is required. Recent technology strategies by industries and governments also aim to encourage development of systems with a higher level of autonomy. These factors necessitate an on-board PMS with autonomous operation capability. As a result, an improved integrated PMS capable of constructing optimal, or *good quality*, power supply and delivery plans, on-board and in-operation, is required as part of the technology growth in autonomous systems. Thus, an intelligent PMS, as proposed in Morley and Wall [2010], aims to meet these goals.

Evidence of research in the development of solutions to some of the issues involved in implementing intelligent PMSs within autonomous systems have already been addressed. Mei et al. [2005] proposed a novel strategy to improve power management using dynamic power management and a real-time scheduler. However, it was unclear what specific rules or conditions were applied to enable real-time decision-making mechanisms. Ogawa et al. [2006] proposed a component for electric power control (CEPC) to minimise the power consumption of a small robot architecture. The underlying strategy leads to efficient use of batteries and executing alternative tasks which consume less power, where possible. However, this raises a question of how well the strategy will perform if there is no alternative set of tasks; the potential of this strategy is limited. Zhang et al. [2009] suggested that the power consumption on-board small mobile robots could be reduced by controlling the power sinks, exploiting the behaviour of these sinks. Zhang et al. guarantee optimality if a set of conditions are met and claim that the proposed method outperforms heuristic methods. However, the methods proposed by Zhang et al. focussed on specific components of the system for a specific type of robot; the wider applicability is unclear.

Khare and Singh [2011] proposed a method to manage and optimize the power generation on board hybrid unmanned surface vehicles by utilising an optimization strategy based on priority and cost optimization. However, it is implied that their solution may not be globally optimal and the real-time applicability of this strategy is unknown. Karunarathne et al. [2011] proposed a power and energy management system for a small fuel cell unmanned aerial vehicle. Although initially the study mentions PMS, a power electronic interface, and energy management system, most of the report discusses the energy management system strategy. The power management itself was rather simple. It was assumed that the payload was constant and, should the demands exceed the fuel cell rating, the battery will compensate. The study did not mention or acknowledge any uncertainties that may be present and while deriving the models of required power, efficiencies of many components were assumed constant. Other related studies include Harmon et al. [2005], Styler et al. [2011], Kermani et al. [2012].

In summary, these studies do not fully meet the goals of an intelligent PMS. Although a cross-platform PMS (control of power sources, sinks, and connections) is required to achieve an improved PMS as proposed, this area has not been addressed in detail by the academic literature. Most studies focus on the control of only part of the PMS platform. Many reports also propose strategies for improved power management limited to smaller systems which are not easily transferable to larger, more complex autonomous systems, with multi-power source multi-power sink. In some cases, the techniques used are too problem-specific. There are also other mismatches in research goals in terms of real-time application of the proposed solution (robustness and restricted computing time and power) and capability of adapting to dynamic environments.

Optimization strategies capable of improving today's PMSs and contributing to the development of intelligent PMSs is required. In this paper, we propose a flexible and adaptive PMS, capable of constructing the *best executable* power schedules while satisfying *real-time* requirements. *Best executable* solutions here refer to the best solutions, in terms of pre-determined objective(s) and feasibility, found within the allocated time and resources. This PMS adapts to its dynamic environment by updating the problem description and problem constraints as new events occur, and solves the problem using a three-level optimization strategy. Due to the importance of safety in autonomous systems, the proposed PMS constructs a feasible solution using a constraint satisfaction approach in the first instance. Then, the proposed PMS optimizes this solution using a local search algorithm followed by a global search algorithm to explore the search space for an improved solution. In order to improve the efficiency of the algorithms in the last two levels, the problem is reformulated using convex programming concepts.

In Section 2, briefly contextualises the proposed strategies. The problem formulation is discussed in Section 3. A solution is proposed in Section 4. A case study specifying a power configuration where the proposed PMS is applied is presented in Section 5. Sections 6 analyses the case study results and Section 7 is the conclusion.

2. AN INTEGRATED POWER MANAGEMENT SYSTEM

In our approach to contribute towards an intelligent PMS, considerations are not limited to power, but also information from other subsystems such as advice on system equipment health. The envisaged application highlights safety as an important attribute and typical goals or objectives would be to optimize the efficiency, costs, performance of operation, and life expectancy of the components. Some of these objectives overlap with one another and are complementary, while some are conflicting.

The power supply and delivery from each power source to each power sink is required to be determined subject to a set of requirements, which are treated as constraints. The constraints of the problem are system constraints (e.g. maximum capability of power sources), equipment health constraints (e.g. degradation of components), and task constraints (e.g. required power to be supplied to ensure task completion).

The proposed integrated PMS is targeted for any multi-source, multi-sink power system with special attention to systems intended for autonomous operation. Of course, adjustments are likely to be required for different applications but this is necessary only for the outer layer of the overall strategy.

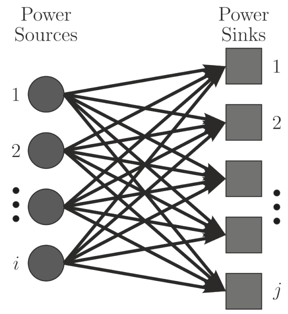

Fig. 1. Example connections between i power sources and j power sinks.

3. PROBLEM FORMULATION

Consider a safety-related system which is operating in a dynamic environment. The power supply and demands across this system change based on tasks at hand, and due to internal and external factors, which may result in infeasibility of the existing power schedule. The integrated PMS aims to update the infeasible power schedule by searching for the best executable power schedule based on pre-defined information and updated information using optimization techniques. This is executed during operation while adhering to time and computational constraints.

We aim to develop strategies suitable for any multi-source, multi-sink system. For illustration purposes, consider a case where there are S power sources available to service the demands of D electrical power sinks. The power schedule for the entire operation time, T, is presented using a series of time intervals, t. The decision variables, x_{ijt}, are the power delivered from each power source, i, to each power sink, j, for each time interval, t. A schematic diagram of the connections is shown in Fig. 1. Each power source has a corresponding rated power output which limits the power available to supply the power sink demands. The new power schedule is expected to be constructed within an allocated run time, e.g. four minutes, while restricted to limited computing resources. While allocating the power delivery between the power sources and power sinks, it is desirable to optimize the fuel consumption. Fuel consumption, the objective for this case, depends on power generation, which is a function of the efficiency of each power source and the decision variables for a particular time interval, x_{ijt}. The power schedule is optimized based on fuel consumption while satisfying system and environmental constraints. To summarise, we wish to:

minimise

$$\sum_{i=1}^{S} \frac{x_{ijt}}{f_{\text{eff}}(x_{ijt})}, for\ j = 1, 2, ..D \tag{1}$$

with respect to x_{ijt}, subject to:

$$0 \leq \sum_{j=1}^{D} x_{ijt} \leq s_{it}, for\ i = 1, 2, ..S \tag{2}$$

$$d_{jt} - \delta^{l}_{jt} \leq \sum_{i=1}^{S} x_{ijt} \leq d_{jt} + \delta^{u}_{jt}, for\ j = 1, 2, ..D \tag{3}$$

where $f_{\text{eff}}(x_{ijt})$ is an efficiency function in terms of x_{ijt}. s_{it} is the maximum available power supply for source i at interval t and d_{jt} is the power demand for sink j at interval t. S and D are the number of available sources and sinks respectively, and t represents the time intervals. The variables δ^{u}_{jt} and δ^{l}_{jt} are the upper and lower tolerances of the power demands, respectively, which are task dependent. The formulation described by (1-3) forms the *default* problem setting.

A power schedule for the entire operation time, T, is required. However, this causes the problem dimension to expand considerably if solved simultaneously. A divide-and-conquer approach is used in which the problem is decomposed into subproblems by separating the whole operation time into N_T time intervals representing different operating phases. These operation phases, or subproblems, are optimized over their corresponding single time interval separately. At the end of the analyses, the solutions to every subproblem are combined to form one solution. This solution is checked to ensure the overall feasibility of the system. There are shortcomings in the sense that, since this non-separable problem is converted to a set of separable problems, the estimated optimal solution may be sub-optimal overall. Arguably, the sub-optimality of the problem is already inevitable due to the real-time requirements of the PMS and the nonconvexity of the overall problem. The advantage of this approach is that it limits the number of decision variables per run, rendering the problem more tractable and allows for an accelerated search for solutions. The decomposition of the problem into subproblems also allows the objective function to be modified at each operation phase according to the system's dynamic environment, thereby increasing the fidelity of the models and system utility.

Change of events during operation introduces the requirement to update the *default* problem setting described above. This may incur changes in (1-3) or introduce new constraints (event specific constraints) to be satisfied. For example, for cases where there is a severed connection between the i^{th} power source and the j^{th} power sink at the t^{th} time interval, the following additional constraint must be satisfied:

$$x_{ijt} = 0. \tag{4}$$

4. OPTIMIZATION STRATEGY

Based on the problem description above, the optimization problem may be categorised as a single-objective non-linear constrained optimization problem with continuous decision variables and a combinatorial component. Another key feature of the problem due to the safety-related nature of the application is the requirement to guarantee feasible solutions within a short time frame e.g. four minutes. Also, the methods selected are required to demonstrate determinacy, transparency, and tractability due to safety requirements. Analytical methods may suit the criteria for safety requirements better than heuristic methods. Nonetheless, the solutions obtained by using heuristic methods may be closer to the true optimal solution. In order to achieve the desired attributes of the improved PMS (e.g. accuracy, speed and determinacy), a compromise of these attributes and hybridisation of methods may be necessary.

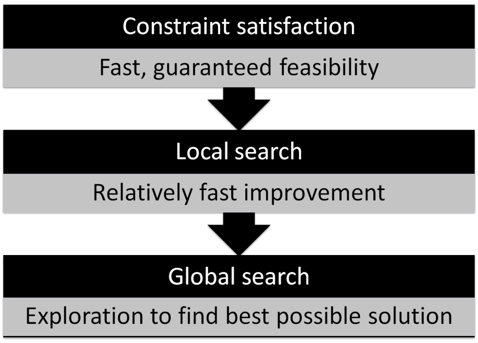

Fig. 2. Three-level approach.

4.1 Optimization solver

A three-level approach is proposed (Fig. 2). First, a constraint satisfaction approach is used to rapidly find a feasible solution based on the available information. Then, a local search algorithm improves the solution obtained in a relatively small amount of time, providing an intermediate solution. Finally, the remaining time is invested in a global search algorithm which searches for the best executable power schedule for the specified problem. Improving the solution in stages enables the best solution during a PMS run to be updated. This is particularly useful if the PMS execution time is reduced during execution, where a solution must be available and ready to be enacted.

Level 1 - Constraint satisfaction: guaranteeing feasibility In Level 1, power demand constraints (3) are assumed to exclude tolerances and these constraints are converted to equality constraints. We argue that demand tolerances are best applied in the optimization levels (only) to obtain benefits from manipulating the power generated. The objective function is also temporarily ignored, applying a strict constraint satisfaction approach. In order to satisfy the equality constraint, the problem is reformulated as:

minimise

$$\sum_{j=1}^{D}((d_{jt} - \sum_{i=1}^{S} x_{ijt})^2) \tag{5}$$

with respect to x_{ijt}, subject to:

$$0 \leq \sum_{j=1}^{D} x_{ijt} \leq s_{it} \tag{6}$$

In the above formulation, minimising (5) seeks to ensure that the power demand equality constraints (3) are satisfied. The resulting solution will be feasible assuming the solution converges and (7) holds, which represents the feasibility of the problem. An analytical method (quadratic programming (Frank and Wolfe [1956])) is used to solve the above problem.

$$\sum_{j=1}^{D} d_{ijt} \leq \sum_{i=1}^{S} s_{it} \tag{7}$$

Level 2 - Local search: an improvement Subsequent to finding a feasible solution, we aim to improve the obtained solution in a short amount of time. Using a local search, a local minimum may be rapidly found. A global minimum is only found if the starting point is sufficiently near the global minimum, i.e. in the global minimum's basin of attraction, or if the problem if unimodal. Although this level often finds a local minimum (for multi-modal functions), it is obtained in a reasonable amount of time and provides an improved solution compared with the solution obtained from Level 1.

A deterministic heuristic technique is proposed to be used for Level 2. Using this class of techniques, the determinacy of Level 2 of the PMS is guaranteed; this is desirable for autonomous systems. The main task of this level is to improve the Level 1 solution, not to search for the global minimum which is often the reason stochastic search is introduced into heuristic techniques. The Nelder-Mead algorithm (Nelder and Mead [1964]) was selected for Level 2 and performs well in finding the nearest minimum while optimizing a nonlinear function. This technique uses the worst point out of an $N+1$ point simplex (N is the number of decision variables) and moves towards the nearest minimum using a set of rules. However, this technique solves unconstrained or box-constrained nonlinear problems. The decision variables of the presented problem have very large bounds. The non-negativity of the decision variables and the maximum capability of the power sources may be applied as the bounds for the decision variables (6). This cannot be directly reduced due to the coupling between the decision variables. Solving (1-3) using this formulation and including penalty terms to handle the constraints was found to be inefficient.

In order to improve the performance of this technique, the problem can be reformulated. A change of variables allows the use of the Nelder-Mead algorithm directly while satisfying the constraints at all times. Since the constraints (2-3) are affine, the decision variables, x, can be redefined to another set that is, by definition, within the convex hull of the constraints (assuming the problem is well posed), producing only feasible solutions. The minimum (or maximum) value for each decision variable, while satisfying (2-3), are determined to form the lower (or upper) bounds using CVX (Grant and Boyd [2013]), a software package for specifying and solving convex programs. Using the concept of convex combinations,

$$\mathbf{x} = C\tilde{\mathbf{w}} \tag{8}$$

where

$$\tilde{\mathbf{w}} = \frac{w_n}{\sum_{n=1}^{2N} w_n} \tag{9}$$

and C represents a matrix containing the bounds for the decision variables, $\mathbf{x}$ is a vector of the original decision variables, $\tilde{\mathbf{w}} \in [0,1]^{2N}$, $w_n \in [0\ 1]$, and N is the number of decision variables, $\mathbf{x}$. The local search algorithm can now solve the problem as a box-constrained optimization problem. The Nelder-Mead algorithm for the reformulated problem now searches for w (with much smaller bounds) while optimizing (1) subject to only event-specific constraints. Using convex combinations in the reformulated problem also guarantee that only feasible solutions (with respect to (2-3)) are explored and (2-3) may be omitted from the optimization process. The efficiency of the Level 2 algorithm is significantly improved by exploiting the convex components of the problem. Penalty terms are added to the objective function to encourage the algorithm to find solutions satisfying event-specific constraints.

Level 3 - Global search: best executable solution A stochastic global search is proposed as the Level 3 algorithm. This level runs for the remaining allowed execution time for the PMS, and explores the search space to find the best executable minimum. Particle swarm optimization (Kennedy and Eberhart [1995]) was selected as the global search algorithm for Level 3 due to its tendency to perform well in dynamic environments as well as its ease of application. Particle swarm optimization solves an optimization problem by updating a swarm of particles (solutions) at every iteration based on each particle's best solution and the swarm's best solution. This is a stochastic search algorithm where random perturbations are enforced to explore the search space, while exploiting the best solutions found so far. The algorithm, which is also an unconstrained optimization solver, solves for w and uses penalty terms in the objective function to manage event-specific constraints (the same formulation as the problem solved by the Level 2 algorithm).

4.2 Three-tiered optimization strategy

The overall structure of the proposed integrated PMS is to:

(1) Update the *default* problem formulation (1-4) and any additional constraints (as required) according to the information provided to the PMS.
(2) Find a feasible solution using a constraint satisfaction technique.
(3) Construct the upper and lower bounds of the decision variables using convex programming based on the default constraints which enables an efficient representation of the problem.
(4) Improve the feasible solution using convex combinations and a local search algorithm.
(5) Invest the remaining execution time in a global search algorithm to find the best attainable solution for the problem.
(6) Select the best executable solution for enactment.

5. CASE STUDY

In this case study, the PMS is connected to a Central Management System (CMS), System Health Management (SHM), and the Power System (PS). The CMS is a centralised controller for the system and informs the PMS of the system status, system requirements, and other information required by the PMS to construct *best executable* power schedules. Additional information, which is informed by the SHM, is also supplied to the PMS. This equipment health information encourages efficient power management based on the system's current health. It is assumed that all the information required is provided to the PMS as needed and the CMS informs the PMS when a new schedule is required. The PMS will be required to construct the best executable power schedule (in terms of fuel consumption and feasibility) describing the power supply and delivery between four power sources and five power sinks within four minutes (Fig. 1). The purpose of this case study is to demonstrate a proof-of-principle of the proposed strategy. *Note: it is necessary to withhold certain details of this case study for reasons of commercial sensitivity.*

Here, a *normal*, or *default*, condition indicates full (equipment) health and maximum rated power rating for the power sources. The system is planned to operate over three phases and is pre-loaded with an offline power schedule. A new event is introduced in *Phase 2* (while the system is in *Phase 1*) which leads to infeasibility of the previous power schedule for the remaining operation time. Thus, a new schedule is required. The integrated PMS is activated as a result of this new event, and a revised best attainable power schedule is constructed.

For this event, Source 4 experiences health issues which decreases the maximum power rating to $42kW$ from $50kW$ while the allowable power demand tolerances remain at 15%. This causes the previous solution to become infeasible. The PMS is notified of this change and a new power schedule is constructed within the allocated four minutes on a representative processing architecture. Table 1 shows the power distribution for *Phase 2* based on the infeasible solution, and the feasible solutions constructed by Level 1-3 of the PMS. The rows represent each power source while each column represents each power source. For example, Source 1 is to supply Sink A with $0.78kW$ based on the previous (infeasible) solution. Table 2 depicts the fuel consumption in kg/s for each phase and algorithm. Implementation was in Matlab vR2011a on Intel Core $3.20GHz$ processor with $4GB$ RAM; the computational constraints were not exceeded for this demonstration.

6. DISCUSSION

Updated solutions for *Phase 2* (Table 1) show that although some components of the new solution were similar to the infeasible solution, others were altered, especially the power setting for the affected power source. In most cases, the small differences are likely to be due to the algorithms optimizing the solutions according to the equipment efficiencies, exploiting allowable demand tolerances. Larger differences, for example, occur in power sources 3 and 4 for both cases. This is likely to be due to wider efficient operating regions for larger power sources compared with the smaller power sources. Recall that the fuel minimisation function incorporates equipment efficiencies and is reflected in the avoidance of maximum loading of the power sources. This is also beneficial to maintaining the life of the equipment since maximum usage will cause additional equipment wear and subsequently reduce equipment life. Only in Level 1 does the PMS ignore these inefficiencies, seeking only to satisfy the constraints, while temporarily ignoring the fuel consumption optimization.

The fuel consumption is reduced as the PMS moves from Level 1 to Level 3 (Table 2). The changes may seem small, however, in large applications, this improvement is capable of significantly reducing the costs of operation. For example, comparing solutions of Level 1 and Level 3 in the case study presented here, which has a 40 hour total operation time, will save approximately $100kg$ of fuel,

Objective value	Phase 2	Phase 3
Level 1 (kg/s)	0.0140	0.0144
Level 2 (kg/s)	0.0134	0.0143
Level 3 (kg/s)	0.0133	0.0143

Table 2. Objective values for *Phases 2 and 3.*

Phase 2		Sink A (kW)	Sink B (kW)	Sink C (kW)	Sink D (kW)	Sink E (kW)	Power generated (kW)
Source 1 (kW)	P	0.78	1.19	1.20	1.18	0.71	5.06 *(6)*
	L1	1.10	0	0	0	0	1.10 *(6)*
	L2	0.92	1.12	1.13	1.11	0.88	5.15 *(6)*
	L3	0.96	1.12	1.12	1.12	0.92	5.25 *(6)*
Source 2 (kW)	P	1.83	2.92	3.52	2.72	1.61	12.58 *(15)*
	L1	0	0	14.00	0	0	14.00 *(15)*
	L2	1.97	3.22	3.24	3.01	1.79	13.23 *(15)*
	L3	1.91	3.22	3.22	2.95	1.67	12.96 *(15)*
Source 3 (kW)	P	3.76	13.41	13.12	9.97	3.53	43.78 *(50)*
	L1	0	32.00	18.00	0	0	50.00 *(50)*
	L2	3.74	14.44	14.56	10.42	3.23	46.39 *(50)*
	L3	3.67	14.12	14.12	10.76	3.44	46.12 *(50)*
Source 4 (kW)	P	3.75	13.57	13.28	10.05	3.13	43.77 *(42)*
	L1	8.90	0	0	24.30	8.80	42.00 *(42)*
	L2	3.47	11.67	11.49	8.96	3.02	38.61 *(42)*
	L3	3.49	11.72	11.72	8.51	2.89	38.31 *(42)*
Power supplied(kW)	P	10.12 *(10)*	31.08 *(32)*	31.11 *(32)*	23.91 *(24.3)*	8.98 *(8.8)*	-
	L1	10.00 *(10)*	32.00 *(32)*	32.00 *(32)*	24.30 *(24.3)*	8.80 *(8.8)*	
	L2	10.10 *(10)*	30.45 *(32)*	30.41 *(32)*	23.50 *(24.3)*	8.92 *(8.8)*	
	L3	10.02 *(10)*	30.18 *(32)*	30.18 *(32)*	23.34 *(24.3)*	8.91 *(8.8)*	

Table 1. Power grid: power distribution for *Phase 2*. *P*, *L1*, *L2*, and *L3* represent previous solution, Level 1 solution, Level 2 solution, and Level 3 solution respectively. The numbers in bracket indicates the maximum power available from each power source (in the *Power generated* column) or the power requirement of each power sink (in the *Power supplied* row).

equivalent to 5% of the total fuel available. However, in *Phase 3*, there is no improvement from Level 2 to Level 3. This may be because the PMS may have reached a global minimum at Level 2.

7. CONCLUSION

In order to contribute towards an intelligent PMS, a flexible and adaptive PMS is proposed comprising of a three-level strategy, combining concepts from constraint satisfaction, convex programming and optimization techniques. The optimization strategies in this cross-platform PMS are aimed to suit any real-time power management of complex systems. In the case study presented, the proposed PMS demonstrates the capability to solve and provide *best executable* solutions within real-time requirements.

There are several other attributes of the proposed PMS which are still under development. For example, robustness of solutions is crucial for autonomous systems. Other ongoing work involves extension of the current problem by incorporating complexities (true behaviour and dependencies of other sub-systems) of the system and also improving the current techniques used.

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