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Minimizing System Modification in an Incremental Design Approach
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ABSTRACT
In this paper we present an approach to mapping and scheduling of distributed embedded systems for hard real-time applications, aiming at minimizing the system modification cost. We consider an incremental design process that starts from an already existing system running a set of applications. We are interested to implement new functionality so that the already running applications are disturbed as little as possible and there is a good chance that, later, new functionality can easily be added to the resulted system. The mapping and scheduling problem are considered in the context of a realistic communication model based on a TDMA protocol.

Keywords: design space exploration, design reuse, distributed real-time systems, process mapping and scheduling, methodology.

1. INTRODUCTION
Distributed embedded systems with multiple processing elements are becoming common in various application areas [4]. In [12], for example, allocation of processing elements, as well as process mapping and scheduling for distributed systems are formulated as a mixed integer linear programming (MILP) problem. A disadvantage of this approach is the complexity of solving the MILP problem. Therefore, alternative problem formulations and solutions based on efficient heuristics have been proposed [1, 2, 8, 14].

Although much of the above work is dedicated to specific aspects of distributed systems, researchers have often ignored or very much simplified issues concerning the communication infrastructure. One notable exception is [13], in which system synthesis is discussed in the context of a distributed architecture based on arbitrated busses. Many efforts dedicated to communication synthesis have concentrated on the synthesis support for the communication infrastructure but without considering hard real-time constraints and system level scheduling aspects [6, 10, 9].

Another characteristic of research efforts concerning the code-sign of embedded systems is that authors concentrate on the design, from scratch, of a new system optimized for a particular application. For many application areas, however, such a situation is extremely uncommon and only rarely appears in design practice. It is much more likely that one has to start from an already existing system running a certain application and the design problem is to implement new functionality (including also upgrades to the existing one) on this system. In such a context it is very important to make as few as possible modifications to the already running applications. The main reason for this is to avoid unnecessarily large design and testing times. Performing modifications on the (potentially large) existing applications increases design time and, even more, testing time (instead of only testing the newly implemented functionality, the old application, or at least a part of it, has also to be retested). However, this is not the only aspect to be considered. Such an incremental design process, in which a design is periodically upgraded with new features, is going through several iterations. Therefore, after new functionality has been implemented, the resulting system has to be structured such that additional functionality, later to be mapped, can easily be accommodated.

We consider mapping and scheduling for hard real-time embedded systems in the context of a realistic communication model. Because our focus is on hard real-time safety critical systems, communication is based on a time division multiple access (TDMA) protocol as recommended for applications in areas like, for example, automotive electronics [7]. For the same reason we use a non-preemptive static task scheduling scheme.

In this paper, we have considered the design of distributed embedded systems in the context of an incremental design process as outlined above. This implies that we perform mapping and scheduling of new functionality so that certain design constraints are satisfied and:

- already running applications are disturbed as little as possible;
- there is a good chance that new functionality can, later, easily be mapped on the resulted system.

In [11] we have discussed an incremental design strategy which excludes any modifications on already running applications. In this paper we extend our approach in the sense that remapping and scheduling of currently implemented applications are allowed, if they are needed in order to accommodate the new functionality. In this context, we propose a heuristic which finds the set of old applications which have to be remapped together with the new one such that the disturbance on the running system (expressed as the total cost implied by the modifications) is minimized. Once this set of applications has been determined, mapping and scheduling is performed according to the requirements stated above.

Supporting such a design process is of critical importance for current and future industrial practice, as the time interval between successive generations of a product is continuously decreasing, while the complexity due to increased sophistication of new functionality is growing rapidly.

The paper is divided into 6 sections. The next section presents some preliminary discussion. Section 3 introduces the detailed problem formulation and the quality metrics we have defined. Our mapping and scheduling strategies are outlined in Section 4, and the experimental results are presented in Section 5. The last section presents our conclusions.

2. PRELIMINARIES
2.1 System Architecture
We consider architectures consisting of processing nodes connected by a broadcast communication channel. Communication between nodes is based on a TDMA protocol such as the TTP [7] which integrates a set of services necessary for fault-tolerant real-time systems. The communication channel is a broadcast channel, so a message sent by a node is received by all the other nodes. Each node $N_i$ can transmit only during a predetermined time interval, the so called TDMA slot $S_i$ (Figure 1). In such a slot, a node can send several messages packaged in a frame. A sequence of slots corresponding to all the nodes in the architecture is called a TDMA round. A node can have only one slot in a TDMA round. Several TDMA rounds can be combined together in a cycle that is repeated periodically.

We have designed a software architecture which runs on the CPU in each node, and which has a real-time kernel as its main component. Each kernel has a schedule table that contains all the information needed to take decisions on activation of processes and transmission of messages, based on the current value of time [3].

![Figure 1. Buss Access Scheme](image-url)
2.2 The Process Graph

As an abstract model for system representation we use a directed, acyclic, polar graph \( G(V, E) \). Each node \( P_i \in V \) represents one process. An edge \( e_{ij} \in E \) from \( P_i \) to \( P_j \) indicates that the output of \( P_i \) is the input of \( P_j \). A process can be activated after all its inputs have arrived and it issues its outputs when it terminates. Once activated, a process executes until it completes. Each process graph \( G \) is characterized by its period \( T_G \) and its deadline \( D_G \leq T_G \). The functionality of an application is described as a set of process graphs.

2.3 Application Mapping and Scheduling

Considering a system architecture like the one presented in section 2.1, the mapping of a process graph \( G(V, E) \) is given by a function \( M: V \rightarrow PE \), where \( PE = \{N_1, N_2, \ldots, N_{npe}\} \) is the set of nodes (processing elements). For a process \( P_i \in V \), \( M(P_i) \) is the node to which \( P_i \) is assigned for execution. Each process \( P_i \) can potentially be mapped on several nodes. Let \( N_i \subseteq PE \) be the set of nodes to which \( P_i \) can potentially be mapped. For each \( N_i \subseteq N_{npe} \), we know the worst case execution time \( T_{Gi} \) of process \( P_i \), when executed on \( N_i \).

In order to implement an application, represented as a set of process graphs, the designer has to map the processes to the system nodes and to derive a schedule such that all deadlines are satisfied. However, finding a valid schedule is not always possible, either because there are not enough available hardware resources, or the resources are not intelligently allocated to the already running applications. Thus, in order to produce a valid solution, the resources have to be reallocated through rescheduling and remapping of some of the already running applications or, in the worst case, the architecture has to be modified by adding new resources.

In Figure 2 we consider a single processor system with three applications, \( A \), \( B \), and \( C \), each with a deadline \( D_A, D_B \) and \( D_C \). Application \( C \) is depicted in more detail, showing the two processes \( P_1 \) and \( P_2 \) it is composed of. Let us suppose that the already running applications are \( A \) and \( B \), and we have to implement \( C \) as a new application. If \( A \) and \( B \) have been mapped and schedules like in Figure 2a, we will not be able to map application \( C \) (in particular, process \( P_2 \)). With a mapping of \( A \) and \( B \) like in Figure 2b and c, we are able to map both processes of \( C \), but no schedule can be produced which meets the deadline \( D_C \). If \( A \) and \( B \) are implemented like in Figure 2d, application \( C \) can be successfully implemented. Two aspects can be highlighted based on this example:

1. If applications \( A \) and \( B \) are implemented like in Figure 2a (or like in 3b or 3c), it is possible to correctly implement application \( C \) only with modifying the implementation of application \( B \).

2. If during implementation of application \( B \) we would have taken into consideration that sometimes in the future an application like \( C \) will have to be implemented, we could have produced a schedule like the one in Figure 2d. In this case, application \( C \) could be implemented without any modification of an existing application.

3. PROBLEM FORMULATION

We model an application \( \Gamma_{current} \) as a set of process graphs \( \Gamma \in \Gamma_{current} \), each with a period \( T_G \) and a deadline \( D_G \leq T_G \). For each process \( P_i \) in a process graph, we know the set \( N_i \) of potential nodes on which it could be mapped and its worst case execution time on each of these nodes. The underlying architecture is as presented in section 2.1. We consider a non-preemptive static cyclic scheduling policy for both processes and message passing.

Our goal is to map and schedule an application \( \Gamma_{current} \) on a system that already implements a set \( \Psi \) of applications, considering the following requirements:

- a) \[ \begin{array}{c|c|c} D_A & D_B & D_C \end{array} \]
- b) \[ \begin{array}{c|c|c} A & B & C \end{array} \]
- c) \[ \begin{array}{c} Slack \end{array} \]
- d) \[ \begin{array}{c|c} P_1 \end{array} \]

Figure 2. Example for the First Design Criterion

1. If a set of applications have a circular dependence, such that the modification of any one implies the remapping of all the others in that set, the set will be represented as a single node in the graph.
3.2 Characterizing Future Applications
What do we suppose to know about the family \( \Gamma_{\text{future}} \) of applications which do not exist yet? Given a certain limited application area (e.g. automotive electronics), it is not unreasonable to assume that, based on the designers’ previous experience, the nature of expected future functions to be implemented, profiling of previous applications, availability of uncomplete designs for future versions of the product, etc., it is possible to characterize the family of applications which could possibly be added to the current implementation. This is an assumption which is basic for the concept of incremental design. Thus, we consider that, concerning the future applications, we know the set \( S_{f} = \{t_{\text{min}}, \ldots, t_{\text{max}}\} \) of possible worst case execution times for processes, and the set \( S_{b} = \{b_{\text{min}}, \ldots, b_{\text{max}}\} \) of possible message sizes. We also assume that over these sets we know the distribution function \( f_{Sf}(t) \) and \( f_{Sb}(b) \). For example, we might have worst case execution times \( S_{f} = \{50, 100, 200, 300, 500\} \) ms. If there is a higher probability of having processes of 100 ms, and a very low probability of having processes of 300 ms and 500 ms, then our distribution function \( f_{Sf}(t) \) could look like this: \( f_{Sf}(50)=0.20, f_{Sf}(100)=0.50, f_{Sf}(200)=0.20, f_{Sf}(300)=0.05, \) and \( f_{Sf}(500)=0.05 \).

Another information is related to the period of process graphs which could be part of future applications. In particular, the smallest expected period \( T_{\text{min}} \) is assumed to be given, together with the expected necessary processor time \( t_{\text{need}} \) and bus bandwidth \( b_{\text{need}} \) inside such a period \( T_{\text{min}} \). As will be shown later, this information is used in order to provide a fair distribution of slacks.

The execution times in \( S_{f} \) as well as \( t_{\text{need}} \) are considered relative to the slowest node in the system. All the other nodes are characterized by a speedup factor relative to this slowest node.

3.3 Quality Metrics
A designer will be able to map and schedule an application \( \Gamma_{\text{future}} \) on top of a system implementing \( \psi \) and \( \Gamma_{\text{current}} \), only if there are sufficient resources available. In our case, the resources are processor time and the bandwidth on the bus. In the context of a non-preemptive static scheduling policy, having free resources translates into having free time slots on the processors and having space left for messages in the bus slots. We call these free slots available time on the processor or on the bus, slack. It is the size and distribution of the slacks that characterizes the quality of a certain design alternative from the point of view of its potential to accommodate future applications. In this section we introduce two criteria in order to reflect the degree to which one design alternative meets the requirement b) presented at the beginning of section 3.

The first criterion reflects how well the resultant slack sizes fit to a future application. The slack sizes resulted after implementation of \( \Gamma_{\text{current}} \) on top of \( \psi \) should be such that they best accommodate a given family of applications \( \Gamma_{\text{future}} \), characterized by the sets \( S_{f}, S_{b} \) and the probability distributions \( f_{Sf} \) and \( f_{Sb} \), as outlined before. Let us consider the example in Figure 2, where we have a single processor with the applications \( A \) and \( B \) implemented and a future application \( C \) which consists of the two processes, \( P_{1} \) and \( P_{2} \). It can be observed that the best configuration, taking in consideration only slack sizes, is to have a contiguous slack. Such a slack, as depicted in Figure 2c and d, will best accommodate any future application. However, in reality, it is almost impossible to map and schedule the current application such that a contiguous slack is obtained. Not only is it impossible, but it is also undesirable from the point of view of the second design criterion, discussed below.

The second criterion expresses how well the slack is distributed in time. Let \( P_{i} \) be a process with period \( T_{p} \) that belongs to a future application, and \( M(P_{i}) \) the node on which \( P_{i} \) will be mapped. The worst case execution time of \( P_{i} \) is \( t_{\text{max}}(P_{i}) \). In order to schedule \( P_{i} \) we need a slack of size \( t_{\text{min}}(P_{i}) \) that is available periodically, within a period \( T_{p} \), on processor \( M(P_{i}) \). If we consider a group of processes with period \( T \), which are part of \( \Gamma_{\text{future}} \), in order to implement them, a certain amount of slack is needed which is available periodically, with a period \( T \), on the nodes implementing the respective processes. During implementation of \( \Gamma_{\text{current}} \), we aim for a slack distribution such that the future application with the smallest expected period \( T_{\text{min}} \) and with the expected necessary processor time \( t_{\text{need}} \) and bandwidth \( b_{\text{need}} \) can be accommodated.

We have defined two metrics, \( C_{1} \) and \( C_{2} \), which quantify the degree to which the first and second criterion, respectively, are met. A detailed discussion about these metrics is given in [11].

3.4 Cost Function and Exact Problem Formulation
In order to capture how well a certain design alternative meets the requirement b) stated in section 3, the metrics discussed before are combined in an objective function, as follows:

\[
C = \sum_{i} \left( C_{1}(P_{i}) + C_{2}(P_{i}) \right)
\]

As shown in Figure 4, our mapping and scheduling strategy (MS) has two steps. In the first step we try to obtain a valid solution for \( \Gamma_{\text{current}} \cup \Omega \) so that \( R(\Omega) \) is minimized. Starting from such a solution, a second step iteratively improves on the design in order to minimize the objective function \( C \).

4. MAPPING AND SCHEDULING STRATEGY
As shown in Figure 4, our mapping and scheduling strategy (MS) consists of an algorithm which we call \textit{Initial Mapping and Scheduling}, and an algorithm \( \Gamma_{\text{current}} \) to be implemented on top of \( \psi \). This algorithm is designed to find that subset \( \Omega \equiv \psi \cup \Gamma_{\text{future}} \) of old applications that can be remapped and rescheduled such that we produce a valid solution for \( \Gamma_{\text{current}} \cup \Omega \) and the total cost of implementation \( R(\Omega) \) is minimized. Once such an \( \Omega \) is found, we are interested to minimize the objective function \( C \) for the set \( \Gamma_{\text{current}} \cup \Omega \), considering a family of future applications characterized by the sets \( S_{f} \) and \( S_{b} \), the functions \( f_{Sf} \) and \( f_{Sb} \) as well as the parameters \( t_{\text{min}} \), \( t_{\text{need}} \), and \( b_{\text{need}} \).

4.1 The Initial Mapping and Scheduling
The first step of MS consists of an iteration that tries subsets \( \Omega \equiv \psi \cup \Gamma_{\text{future}} \) with the intention to find that subset \( \Omega \) of old applications that can be remapped and rescheduled such that we produce a valid solution for \( \Gamma_{\text{current}} \cup \Omega \) and the total cost of implementation \( R(\Omega) \) is minimized. Once such an \( \Omega \) is found, we are interested to minimize the objective function \( C \) for the set \( \Gamma_{\text{current}} \cup \Omega \), considering a family of future applications characterized by the sets \( S_{f} \) and \( S_{b} \), the functions \( f_{Sf} \) and \( f_{Sb} \) as well as the parameters \( t_{\text{min}} \), \( t_{\text{need}} \), and \( b_{\text{need}} \).

1 This definition of a valid solution can be relaxed by imposing only the satisfaction of deadlines. In this case, the algorithm in Figure 4 will look after a solution which satisfies the deadlines and \( R(\Omega) \) is minimized; the two additional criteria are only considered optionally.
be addressed. First, the process graphs \( G \not\in \Gamma_{current} \cup \Omega \) are merged into a single graph \( \Gamma_{current} \) by unrolling of process graphs and insertion of dummy nodes [11]. In addition, we have to consider during scheduling the mismatch between the periods of the already existing system and those of the current application. The schedule table into which we would like to schedule \( \Gamma_{current} \) has a length of \( T_{\psi @} \) which is the global period of the system \( \psi \) after extraction of the applications in \( \Omega \). However, the period \( T_{\psi @} \) of \( \Gamma_{current} \) can be different from \( T_{\psi @} \). Thus, before scheduling \( \Gamma_{current} \) into the existing schedule table, the schedule table is expanded to the least common multiplier of the two periods. A similar procedure is followed in the case \( T_{\psi @} > T_{\psi @} \).

4.2 The Basic Strategy

If IMS succeeds in finding a mapping and schedule which meet the deadlines, this is not yet a valid solution. In order to produce a valid solution we iteratively try to satisfy the second design criterion. In terms of our metrics, that means a mapping and scheduling such that \( C_{2}^{\Omega} \geq t_{\text{need}} \) and \( C_{2}^{\Gamma} \geq t_{\text{need}} \). Potential moves can be the shifting of processes inside their [ASAP, ALAP] interval in order to improve the periodic slack. The move can be performed on the same node or to other nodes. Similar moves are considered for messages. \( \text{SelectMove}_{\Omega} \) evaluates these moves with regard to the second design criterion and selects the best one to be performed. Any violation of the data dependency constraints is rectified by moving processes or messages concerned in an appropriate way.

If Step 1 has succeeded, a mapping and scheduling of \( \Gamma_{current} \cup \Omega \) has been produced which corresponds to a valid solution. In addition, \( \Omega \) is such that the total modification cost is as small as possible. Starting from this valid solution, the second step of the MS strategy, presented in Figure 4, tries to improve on the design in order to minimize the objective function \( C \). In a similar way as during Step 1, we iteratively improve the design by successive moves. In [11] we introduced a heuristic with the goal of guiding the moves discussed above. Its intelligence lies in how the moves are selected. For each iteration a set of potential moves is selected by the \( \text{PotentialMove} \) function. \( \text{SelectMove} \) then evaluates these moves with regard to the respective metrics and selects the best one to perform.

4.3 Minimizing the Modification Cost

The first step of our mapping strategy described in Figure 4 iterates on subsets \( \Omega \) searching for a valid solution which also minimizes the total modification cost \( R(\Omega) \). As a first attempt, the algorithm searches for a valid implementation of \( \Gamma_{current} \) without disturbing the existing applications \( \Omega \in \Omega \). If no valid solution is found successive subsets \( \Omega \) produced by the function \( \text{NextSubset} \) are considered, until a terminating condition is met. The performance of the algorithm, in terms of runtime and quality of the solutions produced, is strongly influenced by the implementation of the function \( \text{NextSubset} \) and the termination condition. They determine how the design space is explored while testing different subsets \( \Omega \) of applications.

4.3.1 Exhaustive Search (ES)

In order to find \( \Omega_{\text{best}} \), the simplest solution is to try successively all the possible subsets \( \Omega \subseteq \psi \). These subsets are generated in the ascending order of the total modification cost, starting from \( \Omega \). The termination condition is fulfilled when the first valid solution is generated. Since the subsets are generated in ascending order, according to their cost, the subset \( \Omega \) that first produces a valid solution is the subset with the minimum modification cost.

The generation of subsets is performed according to the graph \( G \) that characterizes the existing applications (see section 3.1). Finding the next subset \( \Omega \), starting from the current one, is achieved by a branch and bound algorithm that in the worst case grows exponentially in time with the number of applications. For the example in Figure 3, the call to \( \text{NextSubset}(\emptyset) \) will generate \( \{ \Gamma_{j} \} \) which has the smallest nonzero modification cost. The next generated subsets, in order, together with their corresponding total modification cost are: \( R(\{ \Gamma_{j} \}) = 50 \), \( R(\{ \Gamma_{j}, \Gamma_{j} \}) = 70 \), \( R(\{ \Gamma_{j} \}) = 90 \), \( R(\{ \Gamma_{j}, \Gamma_{j} \}) = 120 \), \( R(\{ \Gamma_{j}, \Gamma_{j}, \Gamma_{j} \}) = 140 \), \( R(\{ \Gamma_{j}, \Gamma_{j}, \Gamma_{j} \}) = 150 \), and so on. The total number of possible subsets according to the graph \( G \) is 16.

This approach, while finding the optimal subset \( \Omega \), requires a large amount of computation time and can be used only with a small number of applications.

4.3.2 Ad-hoc Solution (AH)

If the number of applications is larger, a possible ad-hoc solution could be based on a greedy strategy which, starting from \( \Omega = \emptyset \), progressively enlarges the subset until a valid solution is produced. The algorithm looks at all the non-frozen applications and picks that one which, together with its dependencies, has the smallest modification cost. If the new subset does not produce a valid solution, it is enlarged by including, in the same fashion, the next application with its dependencies. This greedy expansion of the subset is continued until the set is large enough to lead to a valid solution or no application is left. For the example in Figure 3 the call to \( \text{NextSubset}(\emptyset) \) will produce \( R(\{ \Gamma_{j} \}) = 20 \), and will be successively enlarged to \( R(\{ \Gamma_{j}, \Gamma_{j} \}) = 70 \), \( R(\{ \Gamma_{j}, \Gamma_{j}, \Gamma_{j} \}) = 140 \) \( \Gamma_{j} \) could have been picked as well in this step because it has the same modification cost of 70 as \( \Gamma_{j} \) and its dependence \( \Gamma_{j} \) is already in the subset. \( R(\{ \Gamma_{j}, \Gamma_{j}, \Gamma_{j} \}) = 210 \), and so on.

While this approach finds very quickly a valid solution, if one exists, it is possible that the total modification cost is much higher than the optimal one.

4.3.3 Subset Selection Heuristic (SH)

An intelligent selection heuristic should be able to identify the reasons due to which a valid solution has not been found. Such a failure can have two possible causes: an initial mapping which meets the deadlines has not been produced, or the second criterion is not satisfied.

Let us investigate the first reason. If an application \( \Gamma_{i} \) is to meet its deadline \( D_{i} \), all its processes \( P_{j} \) have to be scheduled inside their [ASAP, ALAP] intervals. \( \text{InitialMappingScheduling} \) fails to schedule a process inside its [ASAP, ALAP] interval if there is not enough slack available on any processor, due to other processes scheduled in the same interval. In this situation we say that there is a
conflict with processes belonging to other applications. We are interested to find out which applications are responsible for conflicts encountered by our $\Gamma_{current}$ and not only that, but also which ones are flexible enough to move away in order to avoid these conflicts.

IMS determines a metric $\Delta_1$ that characterizes the degree of conflict and the flexibility of application $i$ in relation to $\Gamma_{current}$. A set of applications $\Omega$ will be characterized, in relation to $\Gamma_{current}$ by

$$\Delta(\Omega) = \sum \Delta_i.$$

The metric $\Delta(\Omega)$ will be used by our subset selection heuristic if IMS has failed to produce a solution which satisfies the deadlines. An application with a larger $\Delta_i$ is more likely to lead to a valid schedule if included in $\Omega$. In Figure 5 we illustrate how this metric is calculated. Applications $A$, $B$ and $C$ are scheduled on three processors $P_1$, $P_2$ and $P_3$, and our goal is to implement the current application $D$. At a certain moment IMS comes to the point to place process $D_j \in D$. However, it is not able to place $D_j$ inside its $[\text{ASAP}, \text{ALAP}]$ interval $I$, because there is not enough free slack available inside $I$ on any of the processors. We are interested to determine which of the applications $A$, $B$ and $C$ are more likely to lend free slack for $D_j$ if remapped. Therefore, we calculate the slack resulted after we move away from the processes inside $I$. For example, the resulted slack available after remapping application $C$ (moving process $C_1$ to the left or to the right inside its own $[\text{ASAP}, \text{ALAP}]$ interval $I$) is of size $|I| - \min(|C_i^b|, |C_i^f|)$). Thus, we increment $\Delta_i$ with $\Delta_c = |I| - \min(|C_i^b|, |C_i^f|) - |D_i^f|$. The increments $\Delta_a$ and $\Delta_b$ to be added to $\Delta_a$ and $\Delta_b$ respectively, are also presented in Figure 5.

IMS continues with the other processes of application $D$ after assuming that process $D_j$ has been scheduled at the beginning of interval $D$. As result of the failed attempt to map $D$, IMS will produce the metrics $\Delta_a$, $\Delta_b$ and $\Delta_c$.

If the initial mapping was successful, the first step of MS could fail during the attempt to satisfy the second criterion. In this case, the metric $\Delta_2$ is computed in a different way. It will capture the potential of an application $i$ to improve the metric $\Gamma_2$ if remapped together with $\Gamma_{current}$. Thus, for the improvement of $C_2$ we consider a total number of moves from all the non-frozen applications (determined using Potential-MoveCost($\psi$)). For each move that has as subject $P_i \in \Gamma_2$, we increment the metric $\Delta_i$ with the predicted improvement on $C_2$.

MS starts by trying an implementation of $\Gamma_{current}$ with $\Omega = \emptyset$. If this attempt fails, because of one of the two reasons mentioned above, the corresponding metrics $\Delta_i$ are computed for all $i \in \psi$. Our heuristic SH will then start by finding the ad-hoc solution $\Omega_{AH}$ produced by the AH algorithm (this will succeed if there exists any solution) with a corresponding cost $R_{AH}=R(\Omega_{AH})$ and a $\Delta_{AH}=\Delta(\Omega_{AH})$. SH now continues by trying to find a solution with a more favorable Omega ($\Omega$ a smaller total cost $R$). Therefore, the thresholds $R_{max}=R_{AH}$ and $\Delta_{min}=-\Delta_{AH}$ (for our experiments we considered $n=2$) are set. For generating new subsets $\Omega$, the function NextSubset now follows a similar approach like ES but in a reverse direction, towards smaller subsets, and it will consider only subsets with a smaller total cost then $R_{max}$ and a larger $\Delta$ then $\Delta_{min}$ (a small $\Delta$ means a reduced potential to eliminate the cause of the initial failure). Each time a valid solution is found, the current values of $R_{max}$ and $\Delta_{min}$ are updated in order to further restrict the search space. The heuristic stops when no subset can be found with $\Delta > \Delta_{min}$ or a certain imposed limit has been reached (e.g. on the total number of attempts to find new subsets).

Figure 5. Metric for the Subset Selection Heuristic

5. EXPERIMENTAL RESULTS

For evaluation of the proposed strategies we first used process graphs of $80, 160, 240, 320$ and $400$ processes, representing the application $\Gamma_{current}$ generated for experimental purpose. $30$ graphs were generated for each graph dimension, resulting in a total of $150$ graphs. We considered an architecture consisting of $10$ nodes. For the communication channel we considered a transmission speed of $256$ kbps and a length below $20$ meters. The maximum length of the data field in a bus slot was $8$ bytes. Experiments were run on a SUN Ultra 10.

The first results concern the quality of the solution obtained with our mapping strategy MS using the search heuristic SH compared to the case when the ad-hoc approach AH and the exhaustive search ES are used. For each of the five graph dimensions for $\Gamma_{current}$ we have considered a set of existing applications $\psi$ consisting of $320, 400, 480, 560$ and $640$ processes, respectively. The sets contained $6, 8, 10$ and $12$ applications, each application with an associated modification cost assigned manually in the range $10$ to $100$. The available slack is of about $50\%$ of the total schedule size. The dependencies between possible subsets $\Omega$ resulted for each set $\psi$ were $32, 128, 256, 1024$ and $4096$. We have considered that the future applications $\Gamma_{future}$ consist of a process graph of $80$ processes, randomly generated according to the following specifications: $S_{20}=\{20, 50, 100, 150, 200\}$ ms, $f_{\psi(S_{20})}=\{10, 25, 45, 15, 5\}$ s, $S_{8}=\{2, 4, 6, 8\}$ bytes, $f_{\psi(S_{8})}=\{20, 50, 20, 10\}$%. $T_{min}=250$ ms, $T_{max}=100$ ms and $b_{\text{seed}}=20$ ms.

MS has been used to produce a valid solution for each of the $150$ process graphs representing $\Gamma_{current}$ on the target system $\psi$ using the ES, AH and SH approaches to subset selection. Figure 6a compares the three approaches based on the total modification cost needed in order to obtain a valid solution. The exhaustive approach ES is able to obtain valid solutions with an optimal (smallest) modification cost, while the ad-hoc approach AH produces in average $3.12$ times more costly modifications in order to obtain valid solutions. However, in order to find the optimal solution ES needs large computation times, as shown in Figure 6b. For example, it can take more than $2$ hours in average to find the smallest cost subset to be remapped that leads to a valid solution in the case of $14$ applications ($640$ processes).

We can see that the proposed heuristic SH performs well, producing close to optimal results with a good scaling for large application sets. For the results in Figure 6 we have eliminated those situations in which no valid solution could be produced by MS.

Another important aspect to be proven by experiments is the extent to which the mapping strategy proposed in the paper really facilitates the implementation of $\Gamma_{future}$ applications. For these experiments we have considered that no modifications are allowed to the applications in $\psi$. We have used an existing set of applications $\psi$ consisting of $400$ processes, with a schedule table of $6$s on each processor, and a slack of about $50\%$ of the total schedule size. Then, we have mapped graphs of $40$, $80$, $160$ and $240$ nodes representing the $\Gamma_{current}$ application on top of $\psi$.

After mapping and scheduling each of these graphs we have tried to add a new application $\Gamma_{future}$ to the resulted system (for $\Gamma_{future}$ we used the same experimental set as presented before). The experiments have been performed twice, using first MS (we call MS the version of MS in which no modification of applications in $\psi$ is allowed), and then an ad-hoc mapping approach (AM), for mapping $\Gamma_{current}$. In both cases we were interested if it is possible to find a valid implementation for $\Gamma_{future}$ on top of $\Gamma_{current}$, using the initial mapping algorithm IMS. The AM approach is a simple, straight-forward solution to produce designs which, to a certain degree, support an incremental process. Starting from the initial valid schedule of length $S$ obtained by IMS for the graph $G$ with $N$ processes, AH uses a simple scheme to redistribute the processes inside the $[0, D]$ interval, where $D$ is the deadline of the process graph $G$. AH starts by considering the first process in topological order, let it be $P_1$. It introduces after $P_1$ a slack of size min/ smallest process size of $\Gamma_{future}$, thus shifting all $P_i$'s descendants to the right. The insertion of slacks is repeated
We are able to map 24 of the 30 future applications, while using AM only 4 of the future applications could be mapped successfully on the current system. If the remaining slack is very small, after we map a $\Gamma_{current}$ of 240, it becomes practically impossible to map new applications without modifying the current system.

If the mapping heuristic is allowed to modify the existing system, as discussed in this paper, then we are able to increase the total number of successfully mapped applications $\Gamma_{future}$ from 65% with MS* to 77.5% with MS. For a $\Gamma_{current}$ with 160 processes the increase is from 60% to 92%. Such an increase is, of course, expected. The important aspect, however, is that it is obtained not by randomly selecting old applications to be remapped, but by performing this selection such that the total modification cost is minimized.

Finally, we considered an example implementing a vehicle cruise controller (CC) modeled using one process graph. The graph has 32 processes and it was to be mapped on an architecture consisting of 4 nodes, namely: Anti Blocking System, Transmission Control Module, Engine Control Module and Electronic Throttle Module. The period was 300 ms, equal to the deadline. In order to validate our approach, we have considered the following setting. The system $\psi$ consists of 80 processes generated randomly, with a schedule table of 300 ms and about 40% slack. The CC is the $\Gamma_{current}$ application to be mapped. We have also generated 30 future applications of 40 processes each with the characteristics of the CC, which are typical for automotive applications. By mapping the CC using MS* we were able to later map 21 of the future applications, while using AM only 4 of the future applications could be mapped. When modifications of the current system were allowed, using MS, we are able to map 24 of the 30 future applications.

6. CONCLUSIONS

We have presented an approach to the incremental design of distributed hard real-time embedded systems. Such a design process satisfies the main requirements when adding new functionality: already running applications are disturbed as little as possible, and there is a good chance that, later, new functionality can easily be mapped on the resulted system. Our approach assumes a non-pre-emptive static cyclic scheduling policy and a realistic communication model based on a TDMA scheme.

We have introduced two design criteria with their corresponding metrics that drive our mapping strategy to solutions supporting an incremental design process. Three algorithms have been proposed to produce a minimal subset of applications which have to be remapped and scheduled in order to implement the new functionality. ES is based on a, potentially slow, branch and bound strategy which finds an optimal solution. AH is very fast but produces solutions that could be of too high cost, while SH is able to quickly produce good quality results. The approach has been validated through several experiments.

REFERENCES