Minimizing Development Cost With Reliability Goal for Automotive Functional Safety During Design Phase

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Abstract—ISO 26262 is a functional safety standard specifically made for automotive systems, in which the automotive safety integrity level (ASIL) is the representation of the criticality level. Recently, most studies have used ASIL decomposition to reduce the development cost of automotive functions. However, these studies have not paid special attention to the problem that the reliability goal may not be satisfied when ASIL decomposition is performed. In this study, we solve the problem of minimizing the development cost of a distributed automotive function while satisfying its reliability goal during the design phase by presenting two heuristic algorithms, reliability calculation of scheme (RCS) and minimizing development cost with reliability goal (MDCRG). We first use RCS to calculate the reliability value of each ASIL decomposition scheme; then, the MDCRG is used to select the scheme with the minimum development cost while satisfying the reliability goal. Real-life benchmark and simulated functions based on real parameter values are used in experiments, and results show the effectiveness of the proposed algorithms.

Index Terms—Automotive functional safety, automotive safety integrity level (ASIL) decomposition, development cost, ISO 26262, reliability goal.

NOMENCLATURE

Acronyms and Abbreviations

ASIL Automotive safety integrity level.
DAG Directed acyclic graph.

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I. INTRODUCTION

A. Background

INCE the invention of the automobile, people have pursued the goal of safe driving. The earliest safety belts, later airbags, and other passive safety measures have saved millions
of lives. The later-developed antilock braking system and other active safety functions greatly enhance the safety of automobiles. However, hazardous events, including systemic failures and random hardware failures in automotive systems, caused by malfunctioning behavior may lead to risks [1]. Risk means the likelihood of injury or damage resulting from these failures and the severity of the consequences of injury or damage [1]. Examples include acceleration, deceleration, and steering; abnormal bounce of the airbag; and doors suddenly opening in high-speed driving. Functional safety is proposed to deal with the above-mentioned risks, and it refers to the absence of unreasonable risk due to hazards caused by malfunctioning behavior of electrical and electronic (E/E) systems [1]. The road vehicles functional safety standard ISO 26262 was officially released in 2011 to adapt to the functional safety of automotive E/E part [1]. ISO 26262 identifies four criticality levels denoted by automotive safety integrity levels (ASILs) (i.e., A, B, C, and D). ASIL refers to a classification of inherent safety goals used to ensure the accomplishment of the goals in the system. ASIL A and ASIL D represent the lowest and highest criticality levels, respectively. ISO 26262 requires designers to evaluate all potential risks in advance and take appropriate measures to maintain the risks in an acceptable scope to ensure the functional safety, particularly active safety functions. Therefore, the core task of modern automotive embedded system design is to ensure the safety-critical function of automotive embedded systems, that is, to maintain normal operations under all kinds of severe conditions and the functional safety of occupants and pedestrians.

### B. Motivation

ISO 26262 defines the exposure for random hardware failures. Exposure means the relative expected frequency of the operational conditions, in which a hazardous event may happen and cause hazard and injury [1]. Exposure thus illustrates the possibility of the occurrence of harm and could affect the reliability of systems. Exposure involves five levels, namely E0, E1, E2, E3, and E4, where E0 represents the lowest level (i.e., incredibly unlikely), and E4 represents the highest level (i.e., high probability, injury could happen under most operating conditions) [1]. Reliability is defined as the probability that the execution is successful [2]–[5]. That is, reliability is just the reverse expression of exposure. If a function satisfies its reliability goal, then this function is considered to be reliable. However, reliability goal is not explicitly defined in ISO 26262, but it can be derived according to the probability values of exposures (please refer to Section III for more details).

The development of safety-critical functions is a highly structured and systematic process dictated by ISO 26262, thereby development cost is generated. Generally, development cost refers to the labor used in the development life cycle of systems, and it is different from resource cost and hardware cost. Increasing development cost is not an option because the automotive industry is a highly cost-sensitive industry for the mass market. ASIL decomposition means that a high-ASIL task can be decomposed into one or more redundant low-ASIL tasks [1], [6], [7]. ISO 26262, Part 9, Section V, provides the guide shown in Fig. 1 for ASIL decomposition [1]. However, ASIL decomposition will affect the reliability and development cost simultaneously.

On the one hand, decomposing a high-ASIL task into several redundant low-ASIL tasks can enhance reliability due to redundancy, such that the reliability goal is easy to be satisfied. On the other hand, decomposing a high-ASIL task to a low ASIL can reduce the development cost by 25%–100% because of the low requirement for low level in the implementation process [6], [7]. However, decomposition is implemented at the expense of adding redundant tasks, such that the total development cost of the redundant low-ASIL tasks is not necessarily less than that of the original high-ASIL task in this situation.

### C. Our Contributions

A development life cycle of a safety-critical function usually involves the analysis, design, implementation, and testing phases. In this study, we aim to minimize the development cost of a distributed automotive function with a reliability goal during the design phase. The main contributions of this study are listed as follows.

1) We present a heuristic algorithm called reliability calculation of scheme (RCS) to calculate the reliability value and development cost of each ASIL decomposition scheme for each task with a low time complexity.

2) We present a heuristic algorithm called minimizing development cost with reliability goal (MDCRG) to select the scheme with the minimum development cost (MDC) while satisfying the reliability goal of the function.

3) We use a real-life benchmark and simulated functions based on real parameter values in experiments and validate the effectiveness of the proposed RCS and MDCRG algorithms.

The rest of this paper is organized as follows. Section II reviews related studies. Section III builds related models. Section IV explains automotive functional safety. Section V presents the RCS algorithm. Section VI presents the MDCRG algorithm. Section VII validates the performance of the presented algorithms. Section VIII concludes this study.
II. RELATED WORK

The primary functional safety standards that are currently in use are the DO178B standard for avionic systems [8], the IEC 61508 standard for all kinds of industrial systems [9], and the ISO 26262 standard for automotive systems [1]. The criticality levels are represented as design assurance level (DAL), safety integrity level (SIL), and ASIL in avionic, industrial, and automotive systems, respectively. Many studies involve these functional safety standards, and the readers can be directed to [10] for a comparison of these standards. In this study, we mainly review related studies on development cost, criticality level decomposition, and the reliability goal.

Software development cost estimation is a widely researched topic. The reader is directed to [11] and [12] for reviews on this topic. One of the most influential software cost models is the constructive cost model [12]. Researchers have shown the consideration of development costs during the design phase of embedded systems [13]. The problem of deciding on the ASIL of a function is typically a manual process performed after hazard analysis and risk assessment. Researchers have started to propose automatic approaches to this problem [14]. A broader view is taken in [15], which proposes a method for the propagation, transformation, and refinement of functional safety requirements. Some studies on SIL decomposition [16], [17] and DAL decomposition [18] are solved to reduce development cost. For example, in [16] and [17], genetic and search-based meta-heuristic algorithms for SIL decomposition are proposed; in [18], a tool called DALculus for the automatic allocation of DALs is presented, such that the smallest DAL may be allocated to a function. The ASIL decomposition for distributed functions was studied recently [6], [7].

As provided in ISO 26262, random hardware failures (also called transient failures in most studies) occur unpredictably during the life of a hardware element, but they follow a probability distribution [1]. A widely accepted reliability model was presented by Shatz and Wang [19], in which the transient failure of each hardware is characterized by a constant failure rate $\lambda$. The failure occurrence of a software task executed on hardware follows a constant-parameter Poisson’s law because the hardware failure probability is extended to overall software [2]–[5], [20].

A function model for the description of distributed end-to-end computations in automobiles is represented by a directed acyclic graph (DAG) [6], [7], [21], [22]. Examples of active safety functions are brake-by-wire and adaptive cruise control [21], [23]. Scheduling tasks with quality of service (QoS) requirement for optimality on multiprocessors is known to be an NP-hard optimization problem [7], [24], [25]. In [26] and [27], Benoit et al. proved that evaluating the reliability of a DAG-based distributed function is an NP-complete problem. In the early development phase, reliability growth becomes critical in supporting decision-making for the overall development program, and [28] proposed a multiobjective, multistage reliability growth planning method. Reliability-aware design techniques and algorithms usually aim to minimize certain objectives while still satisfying the reliability goal. Higher reliability could result in a longer schedule length (or larger energy consumption) of a distributed function, and the problem of optimizing schedule length (or energy consumption) and reliability is considered to be a typical bicriteria optima or Pareto optima problem [29]–[32]. Energy-efficient scheduling with a reliability goal for a function with independent tasks has been studied extensively in [2], [33], and [34]. In [4], a shared recovery-based frequency allocation technique to minimize energy consumption with a reliability goal for a distributed function on a uniprocessor is proposed. All the aforementioned studies were only interested in schedule length or energy consumption minimization with a reliability goal. The recent investigation presented the MaxRe [20] and the RR (i.e., least resources to meet the reliability requirement) [5] algorithms to minimize resource consumption while satisfying the reliability goal of a distributed function on heterogeneous systems. In [35], the DAG_Heu algorithm is presented to minimize the resource cost for a distributed function with a timing constraint and a reliability goal on heterogeneous multiprocessors. However, MaxRe, RR, and DAG_Heu aim at minimizing resource consumption cost, which refers to the resource usage of processors when tasks are running, whereas development cost refers to the labor used in the development life cycle of systems. Therefore, the resource consumption cost and the development cost are two completely different concepts. Generally, development cost is reduced by ASIL decomposition in automotive systems [6], [7] and this is the research object of this paper.

In summary, we know that search algorithms have been developed to solve the problem of development cost reduction. This paper attempts to study this problem with another method. We would like to provide a new design reference for system designers and developers. We know that scheduling tasks with QoS requirement for optimality on multiprocessors is known to be an NP-hard optimization problem. Heuristic list scheduling is a popular method to schedule a DAG-based function in most works. To the best of our knowledge, no research work has employed heuristic list scheduling algorithms to study the problem of development cost reduction with reliability goal for a DAG-based function. In this study, we try to present a heuristic list scheduling to study this problem.

III. AUTOMOTIVE FUNCTIONAL SAFETY

In this section, we introduce some preliminaries of automotive functional safety that are related to ASIL decomposition and reliability goal.

A. Functional Safety Attributes

ISO 26262 defines two important functional attributes, namely severity and exposure. The standard also defines controllability, which represents the current state of the drivers. Severity, exposure, and controllability are mutually orthotropic. Table I shows the classifications of severity, exposure, and controllability in ISO 26262, where exposure is related to reliability. The ASIL determination is based on these three attributes (severity, exposure, and controllability). Table II shows the ASIL
TABLE I
CLASSIFICATIONS OF SEVERITY, EXPOSURE, AND CONTROLLABILITY IN ISO 26262 [1]

<table>
<thead>
<tr>
<th>Severity</th>
<th>Exposure</th>
<th>Controllability</th>
</tr>
</thead>
<tbody>
<tr>
<td>S0</td>
<td>No injuries</td>
<td>E0 Incredibly unlikely</td>
</tr>
<tr>
<td>S1</td>
<td>Light to moderate injuries</td>
<td>E1 Very low probability</td>
</tr>
<tr>
<td>S2</td>
<td>Severe to life-threatening injuries</td>
<td>E2 Low probability</td>
</tr>
<tr>
<td>S3</td>
<td>Life-threatening to fatal injuries</td>
<td>E3 Medium probability</td>
</tr>
<tr>
<td></td>
<td>E4 High probability</td>
<td>C3 Difficult to control or uncontrollable</td>
</tr>
</tbody>
</table>

TABLE II
ASIL DETERMINATION BASED ON SEVERITY, EXPOSURE, AND CONTROLLABILITY IN ISO 26262 [1]

<table>
<thead>
<tr>
<th>Severity</th>
<th>Exposure</th>
<th>Controllability</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>E1 QM QM QM</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E2 QM QM QM</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E3 QM QM A</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E4 QM A B</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td>S2</td>
<td>E1 QM QM QM</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E2 QM QM A</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E3 QM A B</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E4 A B C</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td>S3</td>
<td>E1 QM QM A</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E2 QM A B</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E3 A B C</td>
<td>C1 C2 C3</td>
</tr>
<tr>
<td></td>
<td>E4 B C D</td>
<td>C1 C2 C3</td>
</tr>
</tbody>
</table>

determinations, where D is the highest level, and A is the lowest level. QM is the quality management, and it means that developing a function according to QM is sufficient, without regard to any safety-related design. Note that E0 and C0 do not constitute ASIL because E0 stands for incredibly unlikely (0%), and C0 stands for controllable in general (100%). In general, severity cannot be changed. The reason is that severity is associated with the consequences of a function when risk occurs and has been determined in hazard analysis and during the risk assessment phase. Controllability can be changed because it is decided by the current state of drivers; considering that this study focused on the design phase, we assume that the function is uncontrollable and it is denoted by C3 from a conservative perspective. In this study, if we want to reduce the ASIL of a function, then we need to reduce the exposure.

B. ASIL Decomposition

ISO 26262, Part 9, Section V provides the ASIL decomposition guide and scheme shown in Fig. 1 [1]. The decomposition affects the total development cost and reliability (i.e., successful probability) because a task has different worst case execution times (WCETs) and development costs on different ASILs. We consider a task $n_i$ with ASIL C. According to Fig. 1(c), we can decompose $n_i$ into two redundant tasks, namely $n_1$ with ASIL B and $n_2$ with ASIL A. $n_1$ can be further decomposed into two ASIL A tasks according to Fig. 1(b). As all the WCETs and development costs of tasks must be certified to the highest criticality level ASIL D, we assume that all tasks of the function are first executed on ASIL D, and then each task is replicated to redundant tasks that can be executed in other ASILs through ASIL decomposition. We can obtain all possible schemes of ASIL D as follows.

1) ASIL D itself has three decomposition schemes, ASIL C + ASIL A, ASIL B + ASIL B, and ASIL D, as shown in Fig. 1(d).

2) ASIL C can be decomposed into ASIL B + ASIL A according to Fig. 1(c), thus ASIL C + ASIL A can be further decomposed to ASIL B + 2 × ASIL A, as shown with the arrow from Fig. 2(a) to (d). Similarly, ASIL B + ASIL B can also be further decomposed to ASIL B + 2 × ASIL A, as shown with the arrow from Fig. 2(b) to (d). Therefore, these two decompositions can only be considered as the same result, as shown in Fig. 2(d).

3) ASIL B can be decomposed into ASIL A + ASIL A according to Fig. 1(b), such that ASIL B + 2 × ASIL A can be further decomposed to 4 × ASIL A, as shown with the arrow from Fig. 2(d) to (e). Finally, five ASIL decomposition schemes of ASIL D are obtained as follows: ASIL C + ASIL A, ASIL B + ASIL B, ASIL D, ASIL B + 2 × ASIL A, and 4 × ASIL A, as shown with the arrows from Fig. 2(a) to (e).

Our objective is to choose the best scheme for each task.
C. Exposure and Reliability Goal

ISO 26262 provides the duration/probability of exposure in [1, Table B.2, Annex B of Part 3], as shown in Table III. For example, the probability of exposure E4 is greater than 10% of average operating time. Note that ISO 26262 does not define the concept of reliability goal, but we can deduce the corresponding reliability goals for given exposure levels as mentioned earlier. For example, the probability of exposure E2 is less than 1% of average operating time. That is, the lowest probability of occurrence hazardous event is close to 0.01; to ensure safety, the actual reliability must be larger than or equal to 0.99, which is considered as the reliability goal in this case. The reliability goals for other exposures can also be obtained according to the above rule. Finally, the reliability goals for exposures are shown in Table III.

<table>
<thead>
<tr>
<th>Exposure level</th>
<th>Probability of exposure</th>
<th>Reliability goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1 Very low probability</td>
<td>Not specified</td>
<td>At least exceeds 0.99</td>
</tr>
<tr>
<td>E2 Low probability</td>
<td>&lt;1%</td>
<td>0.99</td>
</tr>
<tr>
<td>E3 Medium probability</td>
<td>[1%, 10%]</td>
<td>&gt;0.9</td>
</tr>
<tr>
<td>E4 High probability</td>
<td>&gt;10%</td>
<td>&lt;=0.9</td>
</tr>
</tbody>
</table>

IV. MODELS

A. System Architecture

Automotive E/E architecture has evolved into heterogeneous distributed integrated architecture because of the size, weight, and power consumption for cost and high-performance benefits [21], [23], [36]. A high-end automotive system comprises at least 70 heterogeneous electronic control units (ECUs) interconnected by a central gateway, and the number of ECUs is expected to increase further in future automotive systems [21], [37].

Similar to [21], we consider a distributed integrated platform as a controller area network (CAN) cluster (also called multidomain CAN systems), where more than four or five CAN buses are integrated by a central gateway, and several ECUs are mounted on each CAN bus. Each ECU contains a central processing unit (CPU), random access memory and nonvolatile memory, and a network interface card [7]. An ECU can execute several tasks with different ASILs and a task can be executed on different ECUs. A task executed completely in one ECU sends messages to all its successor tasks, which may be located in the same ECU or different ECUs of different buses. For example, task $n_1$ is executed on ECU $u_1$ of $CAN_1$. It then sends a message $m_{1,2}$ to its successor task $n_2$ located in $u_6$ of $CAN_3$ (see Fig. 3). The central gateway is a highly important node that connects CAN clusters and allows messages to be passed from one bus to another. $U = \{u_1, u_2, \ldots, u_{|U|}\}$ represents a set of heterogeneous ECUs, where $|U|$ represents the size of set $U$. Note that for any set $X$, this study uses $|X|$ to denote its size.

![Fig. 3. Integrated automotive architecture [21].](image_url)
than that at a low ASIL. Similar to [6], [7], we assume that the development effort for each task on each ASIL has been known because of the systematic nature of the development processes dictated by the standards. In this study, we consider nonpreemptive scheduling for ECUs which can be supported by eCos operating system.

C. Motivating Example

Fig. 4 shows a motivating example of a DAG-based distributed function with six tasks. Weight 9 of the edge between $n_1$ and $n_2$ in Fig. 4 represents the development cost denoted by $c_{1,2} = 9$ if $n_1$ and $n_2$ are not allocated to the same ECU.

Table IV lists the WCETs of each task on four different ECUs $\{u_1, u_2, u_3, u_4\}$ and four different ASILs $\{L_A, L_B, L_C, L_D\}$. Weight 7 of $n_1$, $u_2$, and $L_A$ in Table IV represents the WCET denoted by $w_{1,2,A} = 7$. A task with high ASIL has larger WCET than that with low ASIL on the same ECU as explained earlier. A task with high ASIL has different WCETs on different ECUs because of the heterogeneity of the ECUs.

Table V lists the development costs of each task on four different ASILs $\{L_A, L_B, L_C, L_D\}$. Weight 5 of $n_1$, $L_A$ in Table V represents the development cost denoted by $v_{1,A} = 5$. A task with high ASIL has larger development cost than that with low ASIL as explained earlier.

D. Problem Description

We assume that a distributed function $G$ is given with a known reliability goal $R_{goal}(G)$ that would be executed on a heterogeneous multiple ECUs set $U$ and ASIL set $\{L_A, L_B, L_C, L_D\}$. Then, the problem to be addressed in this study is to allocate an ECU and ASIL for each task replica while reducing the development cost of $G$ and satisfying its reliability goal $R_{goal}(G)$. The formal description is finding the ECU and ASIL allocations of all the tasks to minimize the development cost of the function $G$:

$$DC(G) = \sum_{n_i \in N} DC(n_i)$$  \hspace{1cm} (1)$$

subject to

$$R(G) = \prod_{n_i \in N} R(n_i, u_{pr(n_i)}) \geq R_{goal}(G)$$  \hspace{1cm} (2)$$

where $R(G)$ represents the actual reliability value and will be explained in detail in Section V-A. $DC(n_i)$ represents the development cost of $n_i$.

V. RELIABILITY CALCULATION OF SCHEMES

As the decomposition of ASIL D has five fixed schemes shown in Fig. 2, the work of this study is to select the scheme and corresponding ECUs that minimizes the development cost while satisfying the reliability goal of the function. Therefore, the first problem of this study is how to calculate possible reliability values of schemes.

A. Reliability and Task Replication

Generally, the occurrence of a transient failure for a task in a distributed function follows a Poisson’s distribution [2]–[5], [19], [20], [26]. The reliability of an event in unit time $t$ is denoted by

$$R(t) = e^{-\lambda t}$$

where $\lambda$ is the constant failure rate per time unit for an ECU.

We use $\lambda_k$ to represent the constant failure rate per time unit of the ECU $u_k$. The reliability of $n_i$ executed on $u_k$ and $L_h$ in its execution time is denoted by

$$R(n_i, u_k, L_h) = e^{-\lambda_k w_{i,r_k,h}}$$  \hspace{1cm} (3)$$

and the exposure for $n_i$ without using redundant replication is

$$E(n_i, u_k, L_h) = 1 - R(n_i, u_k, L_h) = 1 - e^{-\lambda_k w_{i,r_k,h}}.$$  \hspace{1cm} (4)$$

This study assumes that the function is implemented as software tasks running on a distributed architecture. Because each task has a certain number of replicas (i.e., redundancy) after ASIL decomposition, and each scheme has a fixed number of replicas, we define $num(scheme_g)$ as the number of replicas of $scheme_g$. As long as one replica of $n_i$ is successfully completed, $n_i$ is reliable. Therefore, the reliability value of $n_i$ with allocated scheme $scheme_g$ is calculated by

$$R(n_i, scheme_g) = 1 - \prod_{x=1}^{num(scheme_g)} \left(1 - R(n_i^{x}, u_{pr(n_i)}, L_{ct(pr(n_i))})\right)$$  \hspace{1cm} (5)$$

where $n_i^x$ represents the $x$th number of replicas of $n_i$, $u_{pr(n_i)}$ and $L_{ct(pr(n_i))}$ represent the allocated ECU and ASIL of $n_i^x$, respectively. Then, the reliability of the distributed function is the product of the reliability values of all tasks and is calculated by

$$R(G) = \prod_{n_i \in N} R(n_i) = \prod_{n_i \in N} R(n_i, scheme_{sc(n_i)})$$  \hspace{1cm} (6)$$
Similarly a task has different WCETs on different ECUs or different ASILs, and the failure rates vary in different ECUs. Therefore, the reliability values are different in (7). As the number of replicas is two in $\text{scheme}_1$, we only need to select two reliability values among eight candidates of (7). To obtain a high reliability value for the scheme, we use the following steps to select reliability values for $n_1$ with $\text{scheme}_1$.

1) We select $R(n_1, u_1, L_A) = 0.96078944$ because it has the maximum reliability value among eight candidates.

2) We then select the second maximum reliability value for $L_C$, and $R(n_1, u_1, L_C) = 0.92311635$ can be selected. However, $u_1$ has been occupied by Step 1). We should select the third maximum reliability value $R(n_1, u_2, L_C) = 0.80251880$, where $u_2$ has not been occupied, given the parallel execution of the distributed function.

Finally, the reliability of $n_1$ with $\text{scheme}_1$ is calculated by (5) as follows:

$$R(n_1, \text{scheme}_1) = 1 - (1 - R(n_1, u_1, L_A))(1 - R(n_1, u_2, L_C))$$

$$= 1 - (1 - 0.96078944)(1 - 0.80251880) = 0.99225665.$$  

C. RCS Algorithm

We presented a heuristic RCS algorithm, as shown in Algorithm 1, to calculate the reliability of each scheme based on the above-mentioned analysis.

The details of the RCS algorithm are explained as follows.

1) In Line 1, RCS obtains the decomposed ASIL map $\text{map}(<\text{scheme}_g>)$ $\langle L_{\alpha}, \text{num}_{\alpha}, >, \langle L_{\beta}, \text{num}_{\beta}, >, \ldots, \langle L_{\gamma}, \text{num}_{\gamma}, > \rangle$ of scheme$ _g$.  

2) In Lines 2–6, RCS calculates $R(n_{\alpha}, u_{\beta}, L_{\gamma})$ using (4), which is similar to the calculation of (7).

3) In Line 7, RCS sorts the reliability values in a list $\text{descending\_reliability\_list}$ by descending order of $R(n_{\alpha}, u_{\beta}, L_{\gamma})$ values.

4) In Lines 8–22, RCS calculates $R(n_{\alpha}, \text{scheme}_g)$ based on the heuristic idea explained in Section V-B to obtain a high reliability value for the scheme as much as possible. The time complexity of the RCS algorithm is analyzed as follows.

1) The reliability of each task on each ECU and decomposed ASIL should be calculated in $O(|U|)$ time (Lines 2–6).

2) The $\text{descending\_reliability\_list}$ should be sorted in $O(|N| \times \log |N|)$ time (Line 7).

3) Calculating $R(n_{\alpha}, \text{scheme}_g)$ should traverse all reliability values and verify the occupied ECUs, which can be performed in $O(|U| \times \log |U|)$ time (Lines 8–21).
Algorithm 1: RCS Algorithm.

Input: $U = \{u_1, u_2, \ldots, u_{|U|}\}, \{L_A, L_B, L_C, \ldots, L_B\}, n_i$ and related values

Output: $R(n_i, scheme_g)$ and related values

1: Obtain the decomposed ASIL map $map(scheme_g)$
   $<$ $\{L_a, num_{a}\}, <L_a, num_{a}> , \ldots, <L_n, num_{n}> >$ of $scheme_g$, where $num_{a}$ represents the number of $L_a$;
2: for (each ASIL $L_h$ $\in$ $map(scheme_g)$) do
3:   for (each ECU $u_k$ $\in$ $U$) do
4:     Calculate $R(n_i, u_k, L_h)$ using (4);
5:   end for
6: end for
7: Sort the reliability values in a list descending_reliability_list by descending order of $R(n_i, u_k, L_h)$ values.
8: while (true) do
9:   $R(n_i, u_k, L_h) \leftarrow$ descending_reliability_list.
10: if ($u_k$ has been occupied by any replica of $n_i$) then
11:   continue;
12: end if
13: if (the number of times to select $L_h$ reaches $num_{i_h}$) then
14:   continue;
15: end if
16: if (the number of times to select any $L_h$ reaches $num_{h}$) then
17:   break;
18: end if
19: $w_{pr}(n_i^t) \leftarrow u_k$;
20: $L_{sc}(n_i^t) \leftarrow L_h$;
21: end while
22: Calculate $R(n_i, scheme_g)$ using (5);

Considering Line 7 occupies the main time, the time complexity of the RCS algorithm is $O(|N| \times \log |N|)$.

VI. MINIMIZING DEVELOPMENT COST WITH RELIABILITY GOAL

As the reliability value of each scheme for each task has been obtained by using the RCS algorithm in the previous section, we can solve the final problem of MDCRG on heterogeneous automotive systems. However, scheduling tasks with QoS requirement for optimality on multiprocessors is known to be an NP-hard optimization problem. List scheduling is a well-known heuristic method with low time complexity for a DAG-based distributed function [21], [37], [38], and it includes two phases. The first phase orders tasks based on the descending order of priorities (task prioritization), whereas the second phase allocates each task to the appropriate ECU (task allocation). Most works use search algorithms to find the decomposition schemes [6], [7], [16], [17]. The limitation of search algorithms is that they are time-consuming. Considering that the automotive industry is cost-sensitive, shortening the function’s development life cycle to reduce development cost is crucial. Therefore, using heuristic list scheduling method with low time complexity to solve the problem is more suitable than search algorithms from a development progress control perspective. In this study, we also use the list scheduling to solve the subject problem by task prioritization and task allocation. Task prioritization takes the existing method explained in Section VI-A, whereas task allocation is decomposed into two subproblems: satisfying the reliability goal and minimizing the development cost, explained in Sections VI-B and VI-C, respectively.

A. Task Prioritization

Similar to [38], [21], and [42], this study uses the upward rank value ($rank_u$) of a task given by (8) as the common task priority standard. We use the highest level ASIL D to determine the task priority according to the ISO 26262 standard because a task has different WCETs on different ASILs. Therefore, all the tasks are ordered according to the decreasing order of $rank_u$:

$$rank_u(n_i) = \frac{\overline{w}_{i,D}}{|U|} + \max_{n_j \in succ(n_i)} \{c_{i,j} + rank_u(n_j)\}$$  \hspace{1cm} (8)$$

where $c_{i,j}$ represents the WCRT of the message $c_{i,j}$ as mentioned earlier. $\overline{w}_{i,D}$ represents the average WCET of task $n_i$ on ASIL D and is calculated by

$$\overline{w}_{i,D} = \left( \sum_{k=1}^{|U|} w_{i,k,D} \right) / |U|.$$  \hspace{1cm} (9)$$

Table VII shows the upward rank values of all the tasks (see Fig. 4). If all the predecessors of $n_i$ have been allocated to the ECUs, then $n_i$ is prepared to be allocated. We assume that two tasks $n_i$ and $n_j$ satisfy $rank_u(n_i) > rank_u(n_j)$. If no precedence constraint exists between $n_i$ and $n_j$, then $n_i$ may not have higher priority than $n_j$. Finally, the task allocation order in $G$ is $\{n_1, n_2, n_3, n_5, n_4, n_6\}$.

<table>
<thead>
<tr>
<th>Task</th>
<th>$n_1$</th>
<th>$n_2$</th>
<th>$n_3$</th>
<th>$n_4$</th>
<th>$n_5$</th>
<th>$n_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$rank_u(n_i)$</td>
<td>117</td>
<td>96</td>
<td>67</td>
<td>38</td>
<td>42</td>
<td>10</td>
</tr>
</tbody>
</table>

B. Satisfying Reliability Goal

The minimum and maximum reliability values can be obtained by traversing all the schemes because the reliability of each task on each scheme can be obtained through Algorithm 1. Both values are calculated by

$$R_{\text{min}}(n_i) = \min_{g \in [1,5]} R(n_i, scheme_g)$$ \hspace{1cm} (9)$$

and

$$R_{\text{max}}(n_i) = \max_{g \in [1,5]} R(n_i, scheme_g)$$ \hspace{1cm} (10)$$

respectively.
The minimum and maximum reliability values of $G$ are calculated by
\[
R_{\text{min}}(G) = \prod_{n_i \in N} R_{\text{min}}(n_i)
\tag{11}
\]
and
\[
R_{\text{max}}(G) = \prod_{n_i \in N} R_{\text{max}}(n_i)
\tag{12}
\]
because the reliability of function $G$ is the product of the reliability values of all the tasks (6).

As mentioned earlier, the reliability goal $R_{\text{goal}}$ should be satisfied during ASIL decomposition. Note that $R_{\text{goal}}(G)$ should be larger than or equal to $R_{\text{min}}(G)$; otherwise, $R_{\text{goal}}(G)$ is always satisfied. Meanwhile, $R_{\text{goal}}(G)$ should be less than or equal to $R_{\text{max}}(G)$; otherwise, $R_{\text{goal}}(G)$ cannot always be satisfied. Hence, this study assumes that $R_{\text{goal}}(G)$ belongs to the scope $R_{\text{min}}(G)$ and $R_{\text{max}}(G)$, namely
\[
R_{\text{min}}(G) \leq R_{\text{goal}}(G) \leq R_{\text{max}}(G).
\tag{13}
\]
In this study, we can obtain the $R_{\text{min}}(G) = 0.43171052$ and $R_{\text{max}}(G) = 0.99452100$ of the motivating distributed function. We assume that the reliability goal is $R_{\text{goal}}(G) = 0.9$.

The strategy of satisfying the reliability goal of the distributed function $G$ is shown as follows. We assume that the task to be allocated is $n_{seq}(j)$, where $seq(j)$ represents the $j$th allocated sequence. Therefore, \{\(n_{seq(1)}, n_{seq(2)}, \ldots, n_{seq(j-1)}\)\} represents the set of tasks that have been allocated, and \{\(n_{seq(j+1)}, n_{seq(j+2)}, \ldots, n_{seq(|N|)}\)\} represents the set of tasks that have not been allocated. To ensure the reliability of the function at each task allocation, we presuppose that each task in \{\(n_{seq(j+1)}, n_{seq(j+2)}, \ldots, n_{seq(|N|)}\)\} is allocated to the scheme with the maximum reliability value. Hence, when allocating $n_{seq(j)}$, the reliability of $G$ is calculated by
\[
R(G) = \prod_{x=1}^{j-1} R(n_{seq(x)}, u_{pr(seq(x))})
\times R(n_{seq(j)}) \times \prod_{y=j+1}^{|N|} R_{\text{max}}(n_{seq(y)}).
\]

Given that $R(G)$ should be larger than or equal to $R_{\text{goal}}(G)$, we have
\[
R(G) = \prod_{x=1}^{j-1} R(n_{seq(x)}, u_{pr(seq(x))})
\times R(n_{seq(j)}) \times \prod_{y=j+1}^{|N|} R_{\text{max}}(n_{seq(y)}) \geq R_{\text{goal}}(G)
\]
namely
\[
R(n_{seq(j)}) \geq \frac{R_{\text{goal}}(G)}{\prod_{x=1}^{j-1} R(n_{seq(x)}) \times \prod_{y=j+1}^{|N|} R_{\text{max}}(n_{seq(y)})}.
\tag{14}
\]

Hence, we let the reliability goal of task $n_{seq(y)}$ be
\[
R_{\text{goal}}(n_{seq(j)}) = \frac{R_{\text{goal}}(G)}{\prod_{x=1}^{j-1} R(n_{seq(x)}) \times \prod_{y=j+1}^{|N|} R_{\text{max}}(n_{seq(y)})}.
\tag{15}
\]
Given that the minimum reliability of $n_{seq(y)}$ is $R_{\text{min}}(n_{seq(y)})$ (calculated by (9)), $R_{\text{goal}}(n_{seq(j)})$ should be updated to
\[
R_{\text{goal}}(n_{seq(j)}) = \max \{R_{\text{goal}}(n_{seq(j)}), R_{\text{min}}(n_{seq(y))}\}.
\tag{16}
\]
Given that the maximum reliability of $n_{seq(y)}$ is $R_{\text{max}}(n_{seq(y)})$ (calculated by (10)), $R_{\text{goal}}(n_{seq(j)})$ should be further updated to
\[
R_{\text{goal}}(n_{seq(j)}) = \min \{R_{\text{goal}}(n_{seq(j)}), R_{\text{max}}(n_{seq(y))}\}.
\tag{17}
\]
Therefore, the reliability goal of the function can be transferred to each task. In other words, we only let $n_{seq(j)}$ satisfy the following constraint:
\[
R(n_{seq(j)}) \geq R_{\text{goal}}(n_{seq(j)}).
\]

Hence, when allocating task $n_{seq(j)}$, we can directly consider the reliability goal $R_{\text{goal}}(n_{seq(j)})$ of $n_{seq(j)}$ and ignore the reliability goal of function $G$. As a result, a low time complexity heuristic algorithm can be achieved.

C. Minimizing Development Cost

We let $DC(n_i, scheme_g)$ represent the development cost of $n_i$ with scheme $scheme_g$. We can obtain the development cost of each scheme shown in Fig. 2, given that each scheme has fixed ASILs, shown as follows:
\[
\begin{align*}
DC(n_i, scheme_1) &= v_{i,C} + v_{i,A} \\
DC(n_i, scheme_2) &= 2v_{i,B} \\
DC(n_i, scheme_3) &= v_{i,B} \\
DC(n_i, scheme_4) &= 2v_{i,A} + v_{i,B} \\
DC(n_i, scheme_5) &= 4v_{i,A}
\end{align*}
\tag{18}
\]
where $v_{i,b}$ represents the development cost of $n_i$ on ASIL $L_h$ as mentioned earlier.

The minimum and maximum development costs of each scheme can be obtained by traversing all the five schemes. Both costs are calculated by
\[
DC_{\text{min}}(n_i) = \min_{g \in \{1, 2, 3, 4, 5\}} DC(n_i, scheme_g)
\tag{19}
\]
and
\[
DC_{\text{max}}(n_i) = \max_{g \in \{1, 2, 3, 4, 5\}} DC(n_i, scheme_g)
\tag{20}
\]
respectively.

We let $scheme_{sec(n_i)}$ represent the allocated scheme of $n_i$. Thus, the total development cost of the distributed function is
\[
DC(G) = \sum_{n_i \in N} DC(n_i) = \sum_{n_i \in N} DC(n_i, scheme_{sec(n_i)}).
\tag{21}
\]
The total development cost of function $G$ is the sum of the development costs of all the tasks. Thus, the minimum and
maximum development costs of $G$ are calculated by

$$DC_{\text{min}}(G) = \sum_{n_i \in N} DC_{\text{min}}(n_i)$$  \hspace{1cm} (22)

and

$$DC_{\text{max}}(G) = \sum_{n_i \in N} DC_{\text{max}}(n_i).$$  \hspace{1cm} (23)

The obtained minimum development value is $DC_{\text{min}}(G) = 106$, and its corresponding reliability value is $0.65648591$. However, 0.65648591 cannot satisfy the reliability value of 0.9, which is the reliability goal of the motivating distributed function. Therefore, we should particularly consider that the reliability goal must be satisfied in ASIL decomposition.

In this study, we can obtain the $R_{\text{min}}(G) = 0.43171052$ and $R_{\text{max}}(G) = 0.99452100$ of the motivating distributed function. We assume that the reliability goal is $R_{\text{goal}}(G) = 0.9$. In the following paragraphs, the algorithm called MDCRG is presented to reduce the development cost of a distributed function while satisfying its reliability goal, as shown in Algorithm 2.

The core idea of MDCRG is that the reliability goal of the function is transferred to each task. Each task only selects the scheme with the MDC while satisfying its reliability goal. The main details are explained as follows.

1. MDCRG obtains the reliability goal of each task before it prepares the tasks to be allocated (Line 9).
2. MDCRG skips the schemes that do not satisfy the reliability goal (Lines 12–14); that is, it does not need to calculate the total reliability of the function and determine whether it satisfies the given reliability goal in each task allocation by traversing all the tasks.
3. MDCRG selects the scheme with the MDC for each task while satisfying the condition $R(n_i, \text{scheme}_{g}) < R_{\text{goal}}(n_i)$ (Lines 15–19).
4. If two schemes have the same development cost, then the scheme with the higher reliability value is selected (Lines 20–24).

The time complexity of the MDCRG algorithm is analyzed as follows. Scheduling all tasks must involve traversing all tasks, which can be done in $O(|N|)$ time. The RCS algorithm is called to calculate the reliability value of each scheme in $O(|N| \times \log |N|)$. Therefore, the time complexity of the MDCRG algorithm is $O(|N|^2 \times \log |N|)$. Thus, MDCRG implements effective development cost minimization without sacrificing time complexity.

D. Example of the MDCRG Algorithm

The process and results of the motivating example using the MDCRG algorithm are illustrated in this section. We assume that the constant failure rates for four ECUs are still shown in Table VI and that the reliability goal is still $R_{\text{goal}}(G) = 0.9$. Table VIII lists scheme allocation of the motivating distributed function using the MDCRG algorithm. Each row shows the selected scheme (denoted by bold text) and the corresponding reliability value and development cost. For example, MDCRG selects scheme scheme$_2$ because it has the MDC of 16 in satisfying the reliability goal of 0.90483742. We note that scheme$_3$ also has the MDC of 16, and its reliability value can also satisfy its reliability goal. However, if two schemes have the same development cost, then the scheme with the higher reliability value is selected. The advantage of such strategy is that the reliability goals of the remaining tasks can be reduced according to (15).

Therefore, the actual reliability value and the final development cost of $n_1$ are $R(n_1) = 0.99040688$ and $DC(n_1) = 16$. All the remaining tasks use the same pattern with $n_1$. Finally, the actual reliability value is $R(G) = 0.918901856$, and the final development cost of function $G$ is $DC(G) = 115$, which are calculated by (2) and (1), respectively.
We observe that the final reliability is $R(G) = 0.918901856 > R_{\text{goal}}(G) = 0.9$. Thus, the reliability goal of the function has been satisfied. The MDC of the function is $DC_{\text{min}}(G) = 115$ k [calculated by (22)] in Section VI-C, which is $9 \, $k less than that using MDCRG. However, the corresponding reliability value for $DC_{\text{min}}(G) = 116$ k is merely $R(G) = 0.65648591$.

Fig. 5 also shows the task mapping of the motivating distributed function $G$ using MDCRG. The tasks with different colors mean that they are executed on corresponding ASILs, where ASIL A, ASIL B, ASIL C, and ASIL D are denoted by green, blue, yellow, and red, respectively. For example, $n_1$ selects the $\text{scheme}_2$ containing two ASIL B executed on two ECU $u_1$ and $u_2$. The reason is that $\text{scheme}_2$ has the MDC of 16 while satisfying $n_1$’s reliability goal of 0.90483742, shown in Table VIII. Finally, the end-to-end response time is 108 ms. Note that the arrows in Fig. 5 represent generated communications between tasks.

### VII. EXPERIMENTS

#### A. Experimental Metrics

Considering that this study aims to minimize the development cost of a distributed automotive function with a reliability goal, performance metrics selected for comparison should be the actual reliability value and final development cost of the function. Meanwhile, computation time (i.e., the time to find a solution) should be included from a development life cycle perspective. The final development cost $DC(G)$ and the actual reliability value $R(G)$ are calculated by (1) and (2), respectively. The computation time is measured from the start time to the end time of an algorithm to find a solution.

Algorithms compared with the proposed MDCRG algorithms are the MDC and genetic algorithm with reliability goal (GARG) algorithms. MDC is obtained by (22) and is optimal because it does not consider a reliability goal or timing constraint. GARG is a genetic algorithm to search an enough optimal solution. Genetic algorithm has been developed to solve the problem of development cost reduction for DAG-based distributed functions. Therefore, we believe that MDC and GARG are suitable as compared algorithms in this study.

Considering that this study focuses on the design phase, the function parameters used in this phase are known based on real deployment. In other words, these values have been obtained in the analysis phase. We use the parameter values of real automotive systems as experimental data. The parameter values of the function used in this study are as follows. The failure rate of each task falls in the range of $10^{-5} – 10^{-3}$ in the time unit of $1 \, \mu$s. The WCETs of the tasks and the WCRTs of the messages fall under the range of 100–1600 $\mu$s. The development cost of each task falls in the range of $€-€30 \, k$. The aforementioned values are generated with uniform distribution.

The distributed functions will be tested on a simulated system based on the above real function parameter values to reflect a real deployment. A main advantage of simulation is that it can greatly reduce life cycle cost during the design phase and effectively provide certain optimization guide to the implementation phase. The simulated system is configured with 16 heterogeneous ECUs by creating 16 ECU objects based on the known parameter values using Java on a standard desktop computer with 2.6-GHz Intel CPU and 4-GB memory.

Note that the values of experimental results are obtained by executing one run for one function. Many tests with the same parameter values and scales are preformed and show the same regular pattern and relatively stable results. In other words, experiments are repeatable and do not affect the consistency of the results. Considering that GARG is a genetic algorithm and is a randomized method, the experiment needs to be run multiple times and use statistical tests for the analysis of results. We did several experiments using the GARG algorithm, we recorded that GARG is also relatively stable to the results produced by MDC and MDCRG. Therefore, GARG-generated values are also obtained by executing one run for one function.

#### B. Real-Life Benchmark

We use the real-life benchmark of an automotive case study shown in Fig. 6 adopted from [6]. This function consists of six function blocks: engine controller with seven tasks ($n_1 – n_7$), automatic gear box with four tasks ($n_8 – n_{11}$), antilocking brake system with six tasks ($n_{12} – n_{17}$), wheel angle sensor with...
two tasks ($n_{18} - n_{19}$), suspension controller with five tasks ($n_{20} - n_{24}$), and body work with seven tasks ($n_{25} - n_{31}$).

**Experiment 1:** This experiment is conducted to compare the actual reliability values and the final development costs of a real-life function for varying reliability goals. The reliability goal is changed from 0.9 to 0.99 with a 0.01 increment because values of reliability goals fall in the range of exposure E3 and E2 (see Table III). Meanwhile, the maximum reliability goal for the function is set as 0.99999999, which belongs to the reliability goal in E1.

Fig. 7 shows the actual reliability values of the real-life function for varying reliability goals. The following observations are found.

1) The minimum and maximum reliability values calculated by (11) and (12) are 0.753075 and 0.999999999, respectively.
2) In all the cases, the actual reliability values using the MDCRG and GARG algorithm can always satisfy and are very close to the corresponding reliability goals. The maximum difference between actual reliability values and reliability goals are merely 0.006 and 0.0001 for MDCRG and GARG, respectively.
3) In all the cases, the actual reliability values using the MDC algorithm are approximately 0.836166, which is larger than the minimum reliability value of 0.753075, but they cannot satisfy individual reliability goals.

The above-mentioned results validate that MDC is not designed to satisfy the reliability goals of functions in practice. By contrast, MDCRG and GARG can always satisfy the reliability goals, and the actual reliability values are close to the reliability goals without excessive waste.

Fig. 8 shows the development costs of the real-life function for varying reliability goals, and the following observations are made.

1) The minimum and maximum development costs calculated by (22) and (23) are €592 k and €901 k, respectively. Thus, the development costs using MDC is €592 k.
2) The development costs obtained by MDCRG are not increased linearly with increased reliability goal. The minimum and maximum development costs are €641 k ($R_{\text{goal}} = 0.9$) and €724 k ($R_{\text{goal}} = 0.97$), respectively. The reason could be explained as follows: There are five fixed ASIL decomposition schemes and these schemes could add more redundant tasks for some reliability goals. However, we can select the optimal reliability goal that has MDC in a given interval. For example, some automakers may expect a reliability goal of 0.97, but the actual selected reliability goal will be 0.98 because it generates the
lowest development cost as long as the reliability goal is not less than 0.97.

3) The development costs using MDCRG are higher than the MDCs using MDC. The reason is that MDCRG needs to satisfy its reliability goal and skip some schemes that cannot satisfy the reliability goal of the functions in the task allocation (see Lines 12–19 of Algorithm 2). However, the development costs using MDCRG are still close to the MDCs and are distant from the maximum development costs.

4) The development costs using GARG are always between those using MDC and MDCRG. The reason is that GARG can find the exact MDCs while satisfying given reliability goals, whereas MDCRG is a heuristic list scheduling algorithm to obtain approximate MDCs. The results show that GARG can save as much as 14.5% of development cost than MDCRG.

5) Although development costs are increasing with reliability goals overall, they do not increase linearly. For example, we can easily observe that when the reliability goal is 0.97, the second maximum development cost with €724 k and €644 k increases for MDCRG and GARG, respectively. Such results indicate that larger reliability goals do not lead to lower development costs using MDCRG.

6) Besides some interesting relations between development cost and reliability goal are derived from the experiment results, it would be to assess the efficiency of the MDCRG and GARG algorithms, namely how much time they take to find the results. Our results show that MDCRG merely needs less than 1 s to find the results in all cases. However, GARG needs at least 19 h to find the development cost in each case. As pointed out in Section II, shortening the function’s development life cycle to reduce development cost is crucial during the design phase because automotive industry is cost-sensitive. Therefore, using heuristic list scheduling method is more suitable than genetic algorithm from a development progress control perspective.

C. Simulated Functions With Real Parameter Values

To further validate the effectiveness of the proposed MDCRG algorithm, we use additional simulated functions with the same real parameter values of the real-life function to observe the results.

Experiment 2: The increasing complexity of automotive systems will likely lead to future automotive functions to include at least 50 tasks and may reach 100 tasks. This experiment shows the development costs of functions for varying reliability goals, which are changed from 0.9 to 0.98 with 0.01 increments, because exposure E3 is primarily used in actual system design. The reliability goals can always be satisfied in all cases in Experiment 1. Hence, the reliability values of the functions are no longer provided. Considering that GARG is very time-consuming and more tasks will take more running time, we no longer provide the running time values using GARG.

Figs. 9 and 10 show the development costs of functions with 50 tasks and 100 tasks, respectively, for varying reliability goals. The following observations are made.

1) The minimum and maximum development costs for the function with 50 tasks are €968 k and €1499 k, respectively (see Fig. 9), whereas those for the function with 100 tasks are €1898 k and €2921 k (see Fig. 10). Thus, more tasks need more development costs, which are approximately linearly increased.

2) The development costs for the function with 50 tasks using MDCRG fall under the range of €1080 k and €1281 k (see Fig. 9), whereas those for the function with 100 tasks fall under the range of €1898 k and €2921 k (see Fig. 10). Such results further indicate that the development costs are approximately linearly increased with the increment of tasks.

3) Similar to Experiment 1, the development costs for functions with 50 tasks and 100 tasks using MDCRG still
Fig. 11. Actual reliability values of the real-life function for varying numbers of tasks.

Fig. 12. Development costs (unit: Euros in thousands) of the real-life function for varying numbers of tasks.

do not increase linearly with the increment of reliability goals. When the reliability goal is 0.95, both functions need maximum reliability costs. The minimum reliability cost occurs when the reliability goal is 0.9.

Experiment 3: We are interested in obtaining the results for varying number of tasks of functions with a reliability goal fixed at 0.9, given that MDCRG usually obtains minimum developments cost when the reliability goal is 0.9, which is the least reliability goal of E3. In this experiment, the number of tasks is changed from 20 to 100 with ten increments.

Figs. 11 and 12 show the actual reliability values and development costs of functions for varying number of tasks.

1) Fig. 11 shows that the minimum reliability values and the reliability values using MDC are reduced with the increment of the numbers of tasks. The reason is that the reliability of a function is the product of all its tasks.

2) We find that the reliability values using MDC cannot satisfy the reliability goal of 0.9 in all the cases, whereas those using MDCRG can still always satisfy and are very close to the reliability goal in all the cases. The maximum difference between the actual reliability values and the reliability goals is merely 0.004.

3) All the algorithms would generate increased development costs with the increment of the number of tasks, as shown in Fig. 12, because more tasks could lead to higher development costs. Fortunately, the development costs using MDCRG are still close to the MDCs and are distant from the maximum development costs in all cases, even when the number of tasks is increased.

In summary, combined with the results of real-life and simulated functions, the proposed MDCRG algorithm is effective in minimizing development costs while still satisfying corresponding reliability goals. We believe that MDCRG can effectively explore a part of the design space of development cost during the design phase in the development life cycle of a safety-critical function. Programmers can implement the function according to the ASIL decomposition scheme of each task generated by MDCRG in the later implementation phase.

VIII. CONCLUSION

This study develops an effective development cost minimization solution for a distributed automotive function with a reliability goal on heterogeneous automotive systems by using ASIL decomposition during the design phase. This study presented two heuristic algorithms, RCS and MDCRG, to solve the problem. RCS calculates the reliability value of each ASIL decomposition scheme, and MDCRG transfers the reliability goal of the function to each task and selects the ASIL decomposition scheme with the MDC, while satisfying the reliability goal of the task. MDCRG is validated with real-life and simulated distributed automotive functions in various situations. Considering that the timing constraint is also an important functional safety requirement in real-time embedded systems and has been studied by the state-of-the-art studies in minimizing development cost, our future studies will simultaneously consider the timing constraint and reliability goal to minimize the development cost for distributed automotive functions on heterogeneous architecture. It will be feasible to consider timing requirement and reliability goal one by one in the design phase, or to consider them simultaneously to conduct biobjective optimization.

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