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An Extended Survey and a Comparison Framework for Dataflow Models of Computation and Communication

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Abstract-Dataflow Model of Computation and Communications (DF MoCCs) is a formalism used to specify the behavior of Cyber-Physical Systems (CPSs). DF MoCCs are widely used in the design of CPSs, as they provide a high-level of abstraction to specify the system's behavior. DF MoCCs rules give semantics to a dataflow specification of a CPS, and static analysis algorithms rely on these semantics to guarantee safety properties of the dataflow specification, such as bounded memory usage and deadlock freeness. A wide range of DF MoCCs exists, each with its own characteristics and static analyses. This paper presents a survey of those DF MoCCs and a classification in eight categories. In addition, DF MoCCs are characterized by a comprehensive list of features and static analyses, which reflect their expressiveness and analyzability. Based on this characterization, a framework is proposed to compare the expressiveness and the analyzability of DF MoCCs quantitatively.

Index Terms—Dataflow Model, Survey, Classification, Comparative Study

I. INTRODUCTION

Cyber-Physical Systems (CPSs) are reactive systems that detect environmental shifts through sensors, process this information using computational processes, and then use the output to control actuators. CPSs range from digital signal processing systems to embedded/cloud infrastructures, soft/hard real-time systems, and even a mix of all the above. These complex systems must operate reliably without threatening their internal processes. For example, a failure of the actuator in an autonomous car can lead to catastrophic consequences such as a car crash or a pedestrian accident.

Researchers and engineers seek to understand the behavior of these CPSs and ensure their safety. They develop methods to do so, such as Model of Computation and Communications (MoCCs). A MoCC specifies rules that govern the execution of the system's specification and the communication between its components. Engineers and researchers often use sketches to conceptualize and illustrate systems and ideas in the early stages of development [1]. Block diagrams are a popular informal model for high-level specifications of these systems. A block diagram consists of boxes representing system components and arrows representing the relationship between components. A key advantage of this representation is that it can be fine-grained (e.g., one block specifies a processor instruction) or coarse-grained (e.g., one block is a function or even an aggregation of functions). The first mathematically grounded MoCC based on graphs was independently created by Kahn [2] and Dennis [3], laying the foundations of the DF MoCC family.

Since the seminal work of Lee and Messerschmitt [4], the DF MoCCs family has expanded significantly, now numbering nearly 50 DF MoCC today. Each DF MoCC is a trade-off between its expressiveness -referring to the variety of systems it can specify- and its analyzability, which pertains to the static analyses it can perform. Examples of such static analyses include memory-boundedness, deadlock-freeness, feasibility and schedulability tests.

A framework for comparing DF MoCCs has been proposed in [5]. The fundamental difference between our work and theirs is that in [5], a *denotational semantics* is provided. Actors, channels, and tokens are described in terms of mathematics objects. Our approach has *operational semantics*, i.e., we described the computation capabilities rather than mapping them to a mathematical object. The work of [6] is quite similar but more focused on parametric DF MoCCs.

1) Contributions: The contribution of this paper is an extension of the DF MoCCs survey of [7]. The classification categories have been refined, and the features and static analyses have been updated. As DF MoCCs are a trade-off between their expressiveness and their analyzability, this paper proposes a methodology based on system designer needs to compute the expressiveness and the analyzability score. These scores are two numerical values to evaluate the expressiveness and the analyzability of a DF MoCC.

2) Paper organization: This paper starts by presenting similarities between all DF MoCCs in section II. In section III and section IV, the features and static analyses of our framework are presented, respectively. Some insights about the Turing completeness of DF MoCC are given in section V, and section VI presents our classification and its eight categories. A protocol to compute the expressiveness and analyzability score of a DF MoCC is presented in section VII. Finally, section VIII concludes the paper.

II. DATAFLOW PRINCIPLES

Although each DF MoCC defines its own semantics for specifying and analyzing CPSs, they share the same back-

ground. They are mainly based on the concept of Dataflow Graph (DFG).

Definition 1 (Dataflow Graph). A DFG is a directed graph G = (V, E) that specifies a system where vertices represent actors of the system, and edges represent communication channels between actors. A DFG specifies a system, and the semantics of this DFG is given by the DF MoCC used. We also say that a DFG is an instance or a specification of a DF MoCC.

An *actor* is a computational unit that both produces and consumes data every time it is executed, i.e., every time it executes a *job*. The atomic amount of data exchanged is known as a *token*. Usually, tokens within channels are produced and consumed with a First-In First-Out (FIFO) policy, meaning they are consumed in the order in which they are produced. The internal behavior of an actor may only be partially known by systems designers, and sometimes, it is not at all. Hence, actors lie between "white boxes" and "black boxes". The minimum amount of information system designers need is only the number of tokens produced and consumed by an actor each time it is executed.

Definition 2 (Channel). A channel is formally defined as a tuple $c_i = (v_j, v_k, n_{ij}, n_{ik}, [c_i])$ where v_j is the producer actor, v_k is the consumer actor, n_{ij} is the production rate, *i.e.*, the number of tokens produced by v_j on c_i each time it executes a job, n_{ik} is the consumption rate, *i.e.*, the number of tokens consumed by v_k on c_i each time it executes a job, and $[c_i]$ is the initial tokens of c_i .

DF MoCCs can be classified into *functional deterministic* and *non-functional deterministic* ones. A DF MoCC has a functional determinism if the output of the actors of the DFG solely depends on their inputs, independently from external factors such as time or randomness. The *temporal determinism* of a DF MoCC asserts that the execution windows of the actors are fixed and do not vary from one execution to another. In this paper, we will focus on functional determinism; in this paper, a deterministic DF MoCC is a DF MoCC with a functional determinism.

Although both functional deterministic and non-functional deterministic DF MoCCs have static analysis algorithms, the former ones are more accurate. A static analysis permits the prediction of some facets of the runtime behavior of a CPS at compile-time. Those static analyses often rely on the topology of the CPS's specification and the communication pattern among actors. Both of these information are stored in the *topology matrix*.

Definition 3 (Topology matrix). The topology matrix of a DFG G = (V, E) is denoted $G_{\Gamma} = (\gamma_{ij})$. The range rate (e.g, $\mathbb{N}^*, \mathbb{N}, \mathbb{Q}^*$) of γ_{ij} depends on which DF MoCC defines the semantics of the DFG. In any case, γ_{ij} is the consumption/production rate of the actor v_j from/to the channel c_i . If v_j consumes/produces, γ_{ij} is negative/positive.

Definition 4 (Actor). An actor is formally defined as a tuple

 $v_i = (I_i, O_i)$ where $I_i \subseteq E$ is the set of input channels of v_i and $O_i \subseteq E$ is the set of output channels of v_i . Note that I_i and O_i may be empty. If I_i is empty, v_i is a source actor or a sensor, and if O_i is empty, v_i is a sink actor or an actuator.

Unless stated otherwise, an actor can execute if and only if the number of tokens in its input channels is greater than the consumption rate of the channel. Whenever an actor executes, it writes/reads an amount of token equal to the production/consumption rate of the channel. Write operations are non-blocking, i.e., an actor can produce tokens whenever it executes, and read operations are blocking, i.e., an actor consumes tokens only if it executes and if there are enough tokens in the input channels.

Definition 5 (Iteration). An iteration of a DFG is a partially ordered collection of actors' executions that keeps the token distribution of the DFG unchanged.

III. CHARACTERIZATION OF THE EXPRESSIVENESS OF DF MoCCs

Each DF MoCC can specify different characteristics of CPSs, which is closely tied to the attainable *model fidelity* of a DF MoCC. Depending on the CPS being specified, not all DF MoCCs are suitable. We defined those characteristics as *features*, which we will detail in the following sections.

We conducted a survey to identify the most important features. As a result, some features are shared among multiple DF MoCCs, while others are unique to a specific DF MoCC.

Features are classified into three categories based on how they manifest in the DF MoCC. The first category (cf. section III-A) presents 18 features that are either *present-orabsent*, e.g., the possibility of specifying frequency constraint. The second category (cf. section III-B) involves evaluating the range of the production and consumption rates, and the third category (cf. section III-C) involves assessing the rate and topology updates of the DF MoCC. Last but not least, features are not independent; those dependencies are detailed in section III-D.

A. Comprehensive List of Present-or-Absent Features

There are 18 *present-or-absent* features for DF MoCCs. The following sections will detail those features in a lexicographic order and briefly explain each feature.

1) <u>Blocking Factor (BF)</u>: Actors can consume and produce any multiple of their consumption and production rates. That multiple is called the *blocking factor*.

2) <u>Consumption Threshold (CT)</u>: The number of tokens in a channel must exceed a threshold for an actor to consume them. The consumption threshold is usually different from the consumption rate.

3) <u>Global State</u> (GS): A key-value structure is shared among actors.

4) <u>Hierarchy</u> (Hi): Compositionality can be achieved by associating a subgraph to an actor.

5) <u>Initial and Steady Phases (IniSteP)</u>: Actors can have initial phases followed by cyclic ones (cf. the Phase feature below).

6) <u>Initial Tokens (IT)</u>: Tokens can be stored in channels' buffer before the start of the execution of the system.

7) <u>Initialization and Discard of Initial Tokens (IniDisIT)</u>: An explicit mechanism initializes and discards initial tokens at the start and the end of each iteration of the DFG.

8) <u>Multi-Dimensional FIFO (MDF)</u>: Instead of being a single queue, channels' buffer can be described as multi-dimensional lattices.

9) <u>Meta-Model (MM)</u>: Enhance the expressiveness of a non-meta-model DF MoCC with additional rules.

10) <u>Out-of-Order Consumption (OOC)</u>: Out-of-order consumption of tokens is allowed, i.e., the FIFO policy is not enforced.

11) <u>Parameters (Pa)</u>: Production and consumption rates are not necessarily fixed scalars.

12) <u>Phases (Ph)</u>: Production and consumption rates vary from one job to another.

13) <u>Rate as Interval (Ral)</u>: Production and consumption rates are given as intervals.

14) <u>Execution Time (ET)</u>: Actors can have a non-null execution time.

15) <u>Frequency</u> (Freq): Actors can have a frequency constraint.

16) <u>Delay</u> (Del): Actors can have a delay constraint, i.e., the time of their first execution is postponed for a given amount of time.

17) <u>Production and Consumption Instants (PCI)</u>: Specify the time instants when tokens can be produced and consumed.

18) <u>Sliding Window (SW)</u>: Tokens can be consumed with sliding windows through the channels' buffer.

B. Range Rate

The definition of the topology matrix states that the production and consumption range rates depend on the underlying DF MoCC. The *range rate* is the set of values the production and consumption rates can take. It ranges from the simplest, which is the singleton $\{1\}$, to more complex domains such as \mathbb{Q}^* . The former is less expressive as it implies that the production and consumption rates are fixed at 1. The latter is more expressive as it allows the specification of any positive rational number, i.e., an actor produces and consumes a *fractional number* of tokens. The range rate is an element within the following set: $\{\{1\}, \mathbb{N}^*, \mathbb{N}, \mathbb{Q}^*, \Omega\}$. The semantics of the Ω will be detailed later. Intuitively, it means that "any type of object can be produced and consumed".

C. Rate and Topology Updates

The rate and topology updates are measured in two dimensions: the instants at which they can change (the *when*) and the type of the procedure to define new rates (the *how*). Rate updates may induce topology updates. For instance, setting a rate to zero means that no tokens are produced or consumed. Therefore, the associated channel is no longer used if that rate is zero, and the topology is updated.

First, the *when*. Rate and topology updates can change *between* iterations or *within* iterations of the DFG. When it

occurs between iterations, it implies a static behavior of the DFG during an iteration, but it is more restrictive and less expressive as an update within iterations. Second, the *how*. New rate values can be determined either at *compile-time* or at *runtime*. If the set of possible values for rates is fixed at compile-time, the DFG is said to be *statically-oriented*. If this set varies at runtime, the DFG is *runtime-oriented*.

These two dimensions can be combined: the *when* is either *between* or *within* iterations, and the *how* is either *statically-oriented* or *runtime-oriented*. Thus, the rate and topology updates can be classified into four categories: Between Iteration Runtime Oriented (BIRO), Between Iteration Statically Oriented (BISO), Within Iteration Runtime Oriented (WIRO), and Within Iteration Statically Oriented (WISO). A combination of these behaviors is possible if, for instance, some range rates are fixed at compile-time, and others are determined at runtime.

D. Dependencies between Features

The expressiveness of DF MoCCs has been classified into the *range rate* feature, the *rate and topology updates* feature, and 18 *present-or-absent* features, namely Blocking Factor (BF), Consumption Threshold (CT), Global State (GS), Hierarchy (Hi), Initial and Steady Phases (IniSteP), Initial Tokens (IT), Initial and Discard of Initial Tokens (IniDisIT), Multi-Dimensional FIFO (MDF), Meta-Model (MM), Out-of-Order Consumption (OOC), Parameters (Pa), Phase (Ph), Rate as Interval (RaI), Execution Time (ET), Frequency (Freq), Delay (Del), Production and Consumption Instants (PCI), Sliding Windows (SWi).

Those features are not independent. Those dependencies are presented under the form "Feature $i_1 + \ldots +$ Feature $i_n \rightarrow$ Feature $j_1 + \ldots +$ Feature j_n " such that if there is the set of features of the left-hand side, then the set of features of the right-hand side is also present.

- IniDisIT → IT: The presence of a mechanism to explicitly handle the initialization and discard of initial tokens necessarily implies the presence of initial tokens.
- range rate = Q^{*} → Ph: The semantics of a rational rate p/q is that an actor produces and consumes p tokens over q consecutive executions, so the number of tokens produced and consumed may vary from one execution to another.

IV. CHARACTERIZATION OF THE ANALYZABILITY OF DF MOCCS

A. Comprehensive List of Static Analyses

There are 11 static analyses that can be performed on a DFG. The following sections will detail those static analyses in a lexicographic order and provide a brief explanation of each static analysis.

1) <u>Consistency</u> (Co): The existence of an execution in bounded memory is decidable at compile-time.

2) <u>Decidability</u> (Dec): The feasibility of an execution is provable at compile-time.

3) <u>Functional Determinism (FuncDet)</u>: The same sequence of outputs is produced in response to a given sequence of inputs. In other words, outputs do not depend on external factors such as time or randomness.

4) <u>Execution Windows (ExecWin)</u>: The execution window of the actors can be computed at compile-time.

5) <u>Latency</u> (La): The latency of an execution can be computed at compile-time.

6) <u>Liveness</u> (Li): The existence of a deadlock-free execution is decidable at compile-time.

7) <u>Memory</u> (Me): The memory footprint of an execution can be computed at compile-time.

8) <u>Quasi-staticically</u> <u>Sche</u>dulable (QSc): A quasi-static schedule can be derived at compile-time.

9) <u>Statically Schedulable (StaSch)</u>: A static schedule can be derived at compile-time. Usually, there is no limit on the number of cores executing the system. While common in the context of DF MoCCs, this assumption is not so often found in other communities.

10) <u>Strong</u> <u>Consistency</u> (SCo): The boundedness of all executions is decidable at compile-time.

11) <u>Throughput (Th)</u>: The throughput of an execution can be computed at compile-time.

B. Dependencies between Static Analyses

The analyzability of DF MoCCs has been classified into 11 properties: Consistency (Co), Decidability (Dec), Functional Determinism (FuncDet), Execution Windows (ExecWin), Latency (La), Liveness (Li), Memory (Me), Quasi-Static Schedule (QSc), Statically Schedulable (StaSch), Strong Consistency (SCo), and Throughput (Th).

Those properties are not independent. Those dependencies are presented under the form "*Prop* $i_1 + \ldots + Prop$ $i_n \rightarrow Prop$ $j_1 + \ldots + Prop$ j_n " such that if there is the set of properties of the left-hand side, then the set of properties of the right-hand side is also present.

- StaSch → Dec + Co + Li and QSc → Dec + Co + Li: The derivation of a static/quasi-static schedule at compile-time implies that the feasibility is provable, so there exists at least one deadlock-free execution in bounded memory.
- Dec → Co + Li: The feasibility of a system implies that at least one deadlock-free execution exists in bounded memory.
- SCo → Co: The guarantee of memory boundedness of all executions necessarily implies the existence of at least one memory-bounded execution.
- Li → Co + Dec: The liveness of a dataflow specification implies that there exist a deadlock-free execution, so it implies also the consistency and the feasibility of the specification.
- Th → ET and La → ET: Throughput and latency evaluate quantitatively some performance of the system over time, so those two properties imply that actors have execution times.
- ExecWin \rightarrow ET: The computation of execution window length requires the execution time of actors.

 Me → StaSch and Me → QSc: A memory footprint computation needs to know how the channel buffers are used, which implies knowing a static schedule or a quasistatic schedule.

V. CHARACTERIZATION OF THE TURING-COMPLETENESS

Some DF MoCCs are shown to be Turing complete [8], i.e., they can simulate a Turing machine. In particular, the *halting problem* is undecidable for Turing machines. Thus, it is impossible to determine if an execution of an instance of a Turing-complete DF MoCC will stop or not. Consequently, static analyses such as consistency or liveness are generally undecidable for Turing-complete DF MoCCs. However, some Turing-complete DF MoCCs propose restrictions and conditions on their instances to determine safety properties. These will be detailed for DF MoCCs involved.

VI. THE CLASSIFICATION

We propose a new classification of DF MoCCs that is different from the traditional *static*, *reconfigurable*, and *dynamic* DF MoCCs. We propose to classify DF MoCCs for CPSs design and verification into eight categories as follows: Synchronous Dataflow and Related DF MoCCs (table I), Phased-based DF MoCCs (table II), Timed-based DF MoCCs (table III), Boolean-based DF MoCCs (table IV), Scenariobased DF MoCCs (table V), Meta-Models DF MoCCs (table VI), DF MoCCs with Enable and Invoke Capabilities (table VII) and Process network-based DF MoCCs (table VIII).

A. Synchronous Dataflow and Related DF MoCCs

This category includes DF MoCCs which are very similar to the Synchronous Dataflow (SDF). Those similar DF MoCCs can differ from SDF by the range rate, the rate and topology updates, or even have parametric rates. For each DF MoCC of this category, we will detail the differences with SDF.

1) SDF: The roots of DF MoCC can be traced back to their earliest form in [3]. However, the analyzability of this model was limited. SDF [4] has paved the way for the current dataflow paradigm. An SDF specification is a DFG where the production and consumption rates of the channels belong to \mathbb{N}^* . SDF has consistency and liveness checking algorithms, and a static schedule can be derived [9] while optimizing the memory footprint [10]. Reference [11] extends the usual consistency property to the strong consistency property, i.e., deciding whether all executions are bounded. SDF has been extensively researched for its ability to specify various applications, and many works have delved into the memory footprint minimization problem. For instance, a shared buffer memory model is examined in [12], and a buffer merging technique is proposed in [13]. While the memory footprint minimization problem is NP-complete [14], an exact method to solve this problem is proposed in [15] with model-checking. Another approach presented in [16] involves arithmetic manipulations between production and consumption rates and the number of initial tokens to provide the minimum required buffer size, yielding a deadlock-free execution.

2) *HSDF:* The rates' values of an SDF specification can be restricted to $\{1\}$ to yield an Homogeneous Synchronous Dataflow (HSDF) specification [4]. The static analysis algorithms of SDF also apply to HSDF.

3) SSDF: Scalable Synchronous Dataflow (SSDF) [17] aims to improve the implementation efficiency of SDF specifications. It introduces the concept of the *blocking factor*, allowing actors to produce and consume a positive multiple of their consumption and production rates at each execution. This reduces context-switch overhead by performing multiple computations at once. The value of blocking factors is defined at compile-time and cannot be modified at runtime. A detailed investigation into scheduling strategies to maximize throughput and optimize memory footprint has been conducted [18], [19].

4) *BDDF:* Bounded Dynamic Dataflow (BDDF) [20] extends SSDF by introducing dynamic and upper-bounded ports for a set of actors, allowing their rates to change at runtime up to a maximum value. This addresses some limitations of SSDF, such as the possibility of adjusting consumption or production rates to zero for an uncertain number of executions. The value of dynamic ports depends only on current and previous values token values. Therefore, BDDF is deterministic. BDDF includes topology updates, with a Finite State Machine (FSM) used to specify topology configuration, where each state defines a set of connected actors. Note that actors with an SSDF semantics can coexist within a BDDF specification. In addition, given that dynamic ports are upper-bounded, a consistency analysis similar to SDF [9] can be performed.

5) CG: Computation Graphs (CGs) [21] are more general than SDF. In a CG, each channel is also associated with a consumption threshold. Thus, an actor can execute if the number of tokens in its input channel exceeds both the consumption rate *and* the threshold. The authors of [21] studied safety properties different than the usual ones, including the *determinacy*, i.e., the fact that any execution leads to the same result, and the *termination*, i.e., the fact that any execution terminates. This latter is quite different from the liveness, which asserts that a system *can* actually have a non-terminating execution. As the termination property is outside the scope of our interest, we do not consider it. Reference [14, Section 4.7] provides a condition to generate a static schedule of a CG. The main idea is to find a schedule of a semantically equivalent SDF specification.

6) SPDF: Schedulable Parametric Dataflow (SPDF) [22] is an extended version of SDF that incorporates a set of parameters within the range of \mathbb{N}^* and defined at compiletime. These parameters are communicated through a dedicated network integrated at the top of an SPDF specification and are subject to change within an iteration. SPDF is associated with static analysis algorithms to check consistency and liveness, and a quasi-static schedule can be derived.

7) *MDSDF*: Multi-Dimensional Synchronous Dataflow (MDSDF) [23] extends SDF by defining the number of tokens produced and consumed as multi-dimensional lattices. MDSDF is suitable for modeling signal processing applications, such as image processing. Although tokens are multidimensional, we consider that the range rate is \mathbb{N}^* as each dimension is given as a positive integer. A schedule of an MDSDF specification can be determined at compile-time [24]. Reference [25] provides the initial version of MDSDF, where tokens have a rectangular shape, and [23] goes one step further by considering an arbitrary lattice shape. The token shape is essential as it impacts how actors should read and write them.

8) WSDF: Windowed Synchronous Dataflow (WSDF) [26] extends MDSDF by allowing tokens to be consumed with sliding windows. A token is consumed with a specific sampling pattern through a predefined window. A schedule of a WSDF specification can be derived at compile-time.

9) IBSDF: Interface-Based Synchronous Dataflow (IB-SDF) [27] is a hierarchical extension of SDF. An IBSDF specification is an SDF specification with a source and sink node surrounding it. They both behave as an interface to the environment, which eases the hierarchical construction of an IBSDF specification. Each level of the hierarchy is statically analyzable.

10) *RDF*: Reconfigurable Dataflow (RDF) [28] extends SDF by incorporating a *controller* that dictates how and when an SDF specification may be reconfigured. Graph rewrite rules are enforced when particular runtime criteria are met, such as throughput/buffer occupancy dropping/above a given threshold. RDF ensures the consistency and liveness of the original SDF specification and all potential transformations. All possible reconfigurations of an RDF specification do not have to be explicitly stated at design time, and their number can be arbitrarily large or even unbounded.

11) CV-SDF: Computer Vision-Synchronous Dataflow (CV-SDF) [29] extends SDF to simplify the modeling and analysis of computer vision applications. According to the authors, computer vision systems usually have specific requirements when they execute, such as processing frames into chunks, accessing the neighborhood of a pixel, or accessing the previous frame. They propose a new buffer structure (which no longer acts as a FIFO) along with a special consumption rate format that allows the modeling of those requirements. A schedule, as well as the memory usage, can be computed at compile-time.

12) SPBDF: Synchronous PiggyBacked Dataflow (SPBDF) [30] extends SDF by providing a global state. Two types of actors are introduced to handle the update values inside the global state; the first creates the update request, and the second updates the global state. The second actor is the only one who can write in the global state. Other actors are allowed to read the global state when they execute. The authors of [30] provide necessary and sufficient conditions for the consistency of the global state by proving that the global state is written only once per iteration. A static schedule is derivable based on the scheduling techniques of SDF, and the memory footprint of the global state is computable.

13) HDF: Heterochronous Dataflow (HDF) [31] studied the combination between FSMs and DFGs. This approach

allows the refinement of an actor of a DFG into an FSM and conversely. The questions of consistency and liveness are decidable, but it is usually impractical to compute static schedules.

B. Phased-based DF MoCCs

This category includes DF MoCCs which have the *phase* feature. This means that the number of tokens produced and consumed by an actor can vary from one job to another. Depending on the DF MoCC, the pattern of production and consumption can be cyclic or not and defined at compile-time or at runtime.

1) CSDF: The actors of a Cyclo-Static Dataflow (CSDF) [32] specification have cyclic execution function, production, and consumption rates which are established at compile-time. The production and consumption rates change periodically according to the defined cycle. The rates take their values in \mathbb{N} , so some channels may be periodically disabled when the rate is 0. The conversion from a CSDF specification to an HSDF specification [32] provides consistency and liveness checking, and reference [33] provides sufficient conditions to ensure the liveness without transformation into an HSDF specification. Schedules can be derived at compile-time [34], [35].

2) *CDDF:* Cyclo Dynamic Dataflow (CDDF) [36] is a dynamic version of CSDF. The execution function, token ratios, and execution sequence length can vary at runtime. A control token is read at each actor execution to determine its behavior. Restrictions are imposed on using the control token to enhance the analyzability. These restrictions permit to derive conditions about the strong consistency of a CDDF specification and its schedulability. These restrictions also ensure the functional determinism of CDDF.

3) PCG: Phased Computation Graphs (PCGs) [37] extends CSDF and CGs with both consumption thresholds and initialization phases. The rates of PCGs are divided into initial and steady phases. The initial sequence is performed at the beginning of the execution, and the steady sequence, which is cyclic, takes over for the rest of the execution. The authors of [37] demonstrate conditions for consistency and liveness checkings and a lower bound for memory footprint.

4) *FRDF:* Fractional Rate Dataflow (FRDF) [38] is the first DF MoCC with fractional rates. A fractional rate p/q guarantees that p tokens are produced/consumed every q executions. Consequently, some executions may produce/consume multiple tokens while some may not produce/consume any. The execution instances at which production and consumption occur are not fixed, e.g., for any three consecutive executions of an actor with a production rate of 1/3, only one execution produces a token, and it may be the first *or* the second *or* the third, and this pattern may vary at runtime. Therefore, rates and topology updates are classified as WIRO. We will see that another DF MoCC called POLYGRAPH [39], which also has fractional rates, overcomes this limitation by using initial tokens. Interestingly, initial tokens are *not* part of FRDF. Nothing prevents the token's production and consumption pattern

of a fractional rate to depend on external factors. Thus, FRDF is non-deterministic. However, as a coarse-grained production and consumption pattern is guaranteed at compile-time by the fractional rates, a static schedule can be derived, and memory footprint minimization also follows.

C. Timed-based DF MoCCs

This category includes DF MoCCs where the concept of time is present. This can be the specification of execution time, a frequency execution, or even a delay.

1) tSDF: Timed Synchronous Dataflow (tSDF) [40] is an extension of SDF with a function that maps each actor to their execution time. Such a function permits the extension of static analysis algorithms of SDF to throughput and latency analyses. For instance, a trade-off between buffer requirements and throughput constraints is explored in [41], and a linear programming formulation is proposed in [42] to compute the buffer size with optimal throughput, i.e., the maximum throughput without storage constraints. In reference [40] and [43], the authors propose a state-space traversal to find the minimum latency and maximum throughput of an SDF specification, respectively.

2) *tCSDF*: Timed Cyclo-Static Dataflow (tCSDF) [44] extends CSDF with a function that maps each actor's phase with a non-null execution time. Such a function permits the extension of static analysis of CSDF to throughput and latency analyses. Various studies have been conducted on the trade-off between throughput and memory footprint. The authors of [44] propose a heuristic algorithm to perform this trade-off, and reference [45] proposes a design-space exploration of the Pareto points in the throughput/buffer size space. Mixed Integer Linear Programming (MILP) and Min-Max Linear Programming (MMLP) minimized buffer size under throughput evaluation has also been studied using [48]. Static schedules are also derived in reference [35] while optimizing memory footprint [47].

3) $CSDF^a$: Cyclo-Static Dataflow with auto-concurrency $(CSDF^a)$ [49] extends CSDF by providing a mechanism to handle out-of-order token consumption. Mechanisms such as circular buffers or predefined buffers' access patterns limit the overhead induced by simultaneous executions of an actor. The authors explored the trade-off between the maximum concurrent executions and the memory footprint, throughput, and latency. $CSDF^a$ extends CSDF, so the static analysis algorithms of $CSDF^a$ apply to CSDF specification. However, it is unclear if the static analyses of CSDF, such as memory and static schedule, can be applied to an $CSDF^a$

4) *TPDF:* Transaction Parameterized Dataflow (TPDF) [50] extends CSDF. Rates can be parametric and updated between iterations. TPDF also introduces three types of actors: *select-duplicate*, *transaction*, and *clock* actors. *Select-duplicate* replicates its single entry into any combinations of its outputs, *transaction* is the symmetric process, and *clock* actor sends a control token periodically to another actor. This control token defines the execution mode

DF MoCC	Rate updates	Topology updates	Range rate	Features	Static analyses	Turing complete
SDF [4]	never	never	N*	IT	Co [4], [9]–[11]; Dec [9], [10]; FuncDet [4]; Li [4], [9]–[11], [16]; Me [10], [12], [13], [15], [16]; SCo [11]; StaSch [9], [10]	0
HSDF [4]	never	never	{1}	$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$		0
SSDF [17]	never	never	ℕ*	BF IT	Co [17], [18]; Dec [17], [18]; BF FuncDet [17]; Li [17], [18]; IT Me [17]–[19]; StaSch [17]–[19]	
BDDF [20]	never ¹ + WIRO	never ¹ + WIRO	N	BF ¹ IT	Co [20]; Dec ¹ [17], [18]; FuncDet [20]; Me ¹ [17]–[19]; StaSch ¹ [17], [18]	0
CG [21]	never	never	№*	CT IT	Co [14]; Dec [14]; FuncDet [21]; Li [14]; StaSch [14]	0
SPDF [22]	WISO	never	№*	IT Pa	Co [22]; Dec [22]; FuncDet [22]; Li [22]; QSc [22]	0
MDSDF [23]	never	never	№*	IT MDF	IT IDF Co [23], [24]; Dec [23], [24]; FuncDet [23], [24]; Li [23], [24]; StaSch [23], [24]	
WSDF [26]	never	never	ℕ*	IT MDF SWi	Co [26]; Dec [26]; FuncDet [26]; Li [26]; StaSch [26]	0
IBSDF [27]	never	never	№*	Hi IT	Hi IT Co [27]; Dec [27]; FuncDet [27]; Li [27]; StaSch [27]	
RDF [28]	BIRO	BIRO	ℕ*	IT	Co [28]; Dec [28]; FuncDet [28]; Li [28]	0
CV-SDF [29]	never	never	№*	IT	Co [29]; Dec [29]; IT FuncDet [29]; Li [29]; Me [29]; StaSch [29]	
SPBDF [30]	never	never	№*	GS IT	Co [30]; Dec [30]; FuncDet [30]; Li [30]; Me [30]; StaSch [30]	0
HDF [31]	BISO	never	№*	Hi IT	Co [31]; Dec [31]; FuncDet [31]; Li [31]	0

TABLE I FEATURES AND STATIC ANALYSES OF SYNCHRONOUS DATAFLOW AND RELATED DF MOCCS.

¹ only for the "SSDF actors" *Rate and topology updates acronyms*: BISO: Between Iteration Statically Oriented, BIRO: Between Iteration Runtime Oriented WISO: Within Iteration Statically Oriented, WIRO: Within Iteration Runtime Oriented *Features acronyms*: GS: Global State, Hi: Hierarchy, IT: Initial Tokens, MDF: Multi-Dimensional FIFO, SWi: Sliding Windows

Analyzability acronyms: Co: Consistency, Dec: Decidability, FuncDet: Functional Determinism, Li: Liveness, Me: Memory, SCo: Strong Consistency, StaSch: Statically Schedulable

DF MoCC	Rate updates	Topology updates	Range rate	Features	Static analyses	Turing complete
CSDF [32]	WISO	WISO	N	IT Ph	Co [32]; Dec [34], [35]; FuncDet [32]; Li [32], [33]; StaSch [34], [35]	o
CDDF [36]	WIRO	WIRO	\mathbb{N}	IT Ph	Co [36]; Dec [36]; FuncDet [36]; SCo [36]	0
PCG [37]	never	never	N	IniSteP IT Ph	Co [37]; Dec [37]; FuncDet [37]; Li [37]; Me [37]	0
FRDF [38]	WIRO	WIRO	\mathbb{Q}^*	Ph	Co [38]; Dec [38]; Li [38]; Me [38]; StaSch [38]	0

 TABLE II

 Features and static analyses of Phased-based DF MoCCs.

Rate and topology updates acronyms: WISO: Within Iteration Statically Oriented, WIRO: Within Iteration Runtime Oriented

Features acronyms: : , IniSteP: Initial and Steady Phases, IT: Initial Tokens, Ph: Phase

Analyzability acronyms: Co: Consistency, Dec: Decidability, FuncDet: Functional Determinism, Li: Liveness, Me: Memory, SCo: Strong Consistency, StaSch: Statically Schedulable

of the actor that consumes that control token, e.g., waiting for all input data to be available before execution or selecting the data with the highest priority. Under some restrictions, two different execution modes can be used within the same iteration of a TPDF specification, thus allowing topology and some rate updates within iterations. TPDF provides consistency and liveness checking, as well as a scheduling strategy.

5) PolyGraph: POLYGRAPH [51] enhances the semantics of rational rates of FRDF. A rate of p/q means p tokens are produced/consumed every q executions. An actor's execution increases/decreases by $\frac{p}{q}$ the fractional number of tokens in the channels involved. In contrast with FRDF, initials tokens are used to derive a unique execution sequence from a rational rate. An actor may also have a frequency constraint and a delay. Thus, it must execute at that frequency, and its first execution occurs after the delay. A POLYGRAPH specification is statically analyzable in terms of consistency and liveness. Reference [52] also provides execution windows derivation and a schedulability test.

6) Dynamic PolyGraph: Reference [53] presents a dynamic extension of POLYGRAPH. Actors of dynamic POLYGRAPH label tokens with an execution mode. The execution mode an actor consumes defines how those tokens are processed. A peculiarity of dynamic POLYGRAPH is that tokens can be produced with empty content, i.e., they do not carry any meaningful data. Actors consuming such tokens consider that the corresponding input channel is (virtually) disabled. An implicit assumption is that channels must always be active to transit tokens, even if those tokens have empty content. Nevertheless, dynamic POLYGRAPH is statically analyzable in terms of its consistency and liveness.

7) *ppSDF:* Partially Periodic Synchronous Dataflow (ppSDF) [54] extends SDF by allowing a subset of actors to have a frequency constraint but not a phase as in POLYGRAPH.

The authors give some conditions to assert the schedulability of a ppSDF specification.

8) VSDF: Synchronous Dataflow for VLSI (VSDF) [55] extends SDF for specifying Very Large Scale Integration (VLSI) systems. The authors augment the consistency analysis of SDF by including temporal constraints. This analysis includes equations to formalize that tokens produced on a channel at a given time instant are also consumed at this same time instant. Therefore, not only the number of tokens produced and consumed on each channel must be equal, but also the time at which the tokens are produced and consumed must be equal. It is more accurate to specify the timing constraints on production and consumption instant instead of on actors. Indeed, when timing constraints are specified on the actor, the production and consumption instant are within the frequency interval but have no fixed value.

9) $HSDF^a$: Homogeneous Synchronous Dataflow with auto-concurrency (HSDF^a) [56] extends HSDF by determining the consumption order of tokens with static indices independently of the production order. The token produced by the (n + 1)-th job may precede the token produced by the *n*th job in the buffer's channel if the *n*-th job finishes before the (n + 1)-th job. The authors of [56] propose a method to compute the end-to-end latency of HSDF^a specifications. To that end, assigning an execution time is essential. They suggest deriving a timed automaton [57] semantically equivalent to an HSDF^a specification and using a model-checker like UPPAAL [58] to compute the exact end-to-end latency of the initial HSDF^a specification. In addition, as HSDF^a is a restriction of CSDF^a [49], it inherits its analyzability.

10) *ILDF:* Interval-rate Locally-static Dataflow (ILDF) [59] extends SDF by permitting consumption and production rates to be within a finite natural integers interval. The actual rates are determined just before the start of the execution and remain fixed. A schedule and the

worst-case memory footprint can be derived at compile-time. In addition, if the actors' Best-Case Execution Time (BCET) and Worst-Case Execution Time (WCET) are known, the schedule's best-case and worst-case time performance can be computed. Determining the fixed rate before the execution depends on external conditions, e.g., the size of the data to be processed. Therefore, ILDF is not deterministic.

11) VRDF: Variable Rate Dataflow (VRDF) [60] is a parametric extension of SDF that imposes constraints on parameter usage. For instance, a parameter is used by at most two actors, namely the modifier and user. This means that a parameter can be set at each execution of the modifier, even within an iteration of a VRDF specification. The process of determining the new parameter values is not explicitly defined, and it could result from non-determinism procedures. We also assume that the assignment parameter process does not depend on runtime conditions. In a VRDF specification, two actors using the same parameter must have the same entry in the repetition vector. These and other restrictions allow the authors to prove the strong consistency of a VRDF specification. They propose another static analysis to determine the parameters assignation that guarantees the fulfillment of a throughput constraint of a VRDF specification, as well as the associated memory footprint.

12) VPDF: Variable-rate Phased Dataflow (VPDF) [61] extends VRDF. Besides structural constraints similar to the one of VRDF, actors of a VPDF specification have two parameters for each phase: the number of repetitions and the rate of that phase.

13) *RMDF*: Real-time Mode-aware Dataflow (RMDF) [64] builds upon POLYGRAPH by enabling the specification and analysis of CPSs with both timing constraints on some actors and a mode-dependent execution, i.e., an execution with conditional execution branches. An RMDF specification is statically analyzable regarding its consistency and liveness, and the execution window length can be derived to facilitate a feasibility test [64].

D. Boolean-based DF MoCCs

This category includes DF MoCCs where parameters taking their value between 0 and 1 are used to control actors' execution. Those values determine either how actors consume or produce tokens or determine the topology of the DFG.

1) BDF: Boolean-controlled Dataflow (BDF) [65] is one of the first DF MoCC focusing on topological updates. The production/consumption rates of specific actors called *switch/select* are either 0 or 1, and control tokens consumed by those actors determine which port is used. The control tokens enforce a data-dependency behavior. BDF is Turing complete, and this latter result is often used to demonstrate the Turing completeness of other DF MoCCs. The extension of static analyses of SDF to BDF is discussed in [65].

2) *IDF*: Integer-controlled Dataflow (IDF) [65] is a generalization of BDF where control tokens are any integer. Thus, the switch and select actors become *case* and *end-case* actors.

Some static analysis algorithms of BDF can be extended to IDF.

3) BPDF: Boolean Parametric Dataflow (BPDF) [66] combines two parameters: integer parameters express dynamic rates and 2-values parameters (i.e., "boolean parameters") on the channels. Those latter dynamically (des)activate the channels, possibly within iterations of a BPDF specification. In order to preserve the consistency and liveness analysis, boolean parameters are allowed to change at some well-defined points in the executions. An approach to schedule a BPDF specification is also proposed. There is no restriction on how the value of boolean parameters is chosen, so BPDF is not deterministic.

E. Scenario-based DF MoCCs

This category includes DF MoCCs where the execution of the actors is driven by scenarios. All DF MoCCs of this category are derived from or an extension of Scenario-Aware Dataflow (SADF).

1) SADF: A system specified with SADF [67] has a set of *scenarios*. Besides assigning values to parametric rates, a scenario determines the execution times of the actors of an SADF specification. Execution times are chosen from discrete and finite-support probability distributions, which is a key difference from Exponentially timed Scenario-Aware Dataflow (eSADF), which will be described further in the paper. Detectors are a special type of SADF actors that model the control part of the system by dynamically detecting scenarios. The choice of the scenario may be non-deterministic. An SADF specification switches arbitrarily between scenarios even within an iteration of the SADF specification. In such cases, there are *subscenarios* within a scenario. Consequently, a subscenario change in the middle of an iteration may lead to meaningless behavior, and the authors of [67] have defined the strong consistency property of an SADF specification, which ensures each detector executes only once per scenario. Besides a strong consistency analysis, a liveness checking and quantitative evaluation of memory footprint, throughput, and latency have been conducted [68].

2) FSM-SADF: Finite State Machine-based Scenario-Aware Dataflow (FSM-SADF) [69] is a restriction of SADF. As in an SADF specification, the dynamic behavior of a system is also viewed as an evolving sequence of static behaviors specified with an SDF specification. However, scenarios can change only between iterations of an SDF specification of the respective scenario and there are no subscenarios. A nondeterministic FSM specifies the order in which the scenarios occur and the rates of the current scenario. Techniques to compute worst-case throughput and latency are discussed in [70]. An exact computation is provided in [71], while a trade-off between buffer size and throughput is explored in [72]. An FSM-SADF specification is an SADF specification that is strongly consistent. In contrast with SADF, where actors' execution times follow a probability law, the execution times of actors in FSM-SADF are fixed.

 $\label{eq:TABLE III} Features and static analyses of Timed-based DF MoCCs.$

DF MoCC	Rate updates	Topology updates	Range rate	Features Static analyses		Turing complete
tSDF [40]	never	never	N*	ET IT	Co [40], [42]; Dec [40], [42]; FuncDet [32]; La [40]; Li [40], [42]; Me [41], [42]; StaSch [40], [42]; Th [41]–[43]	0
tCSDF [44]	WISO	WISO	N	ET IT Ph	Co [35], [47]; Dec [44]; FuncDet [44]; Li [35], [47]; Me [44]–[47]; StaSch [35], [47], [48]; Th [44]–[48]	0
CSDF ^a [49]	WISO	WISO	N	ET IT OOC Ph	ET Co [32]; Dec [49]; IT FuncDet [49]; La [49]; OOC Li [32]; Me [49]; Ph Th [49]	
TPDF [50]	WISO + WIRO	WISO + WIRO	N	ET Freq IT Pa Ph	Co [50]; Dec [50]; FuncDet [50]; Li [50]; StaSch [50]; Th [63]	0
PolyGraph [39]	WISO	WISO	Q*	Del ET Freq IT Ph	Co [39]; Dec [52]; FuncDet [39]; ExecWin [52], [62]; Li [39]; StaSch [52]	0
Dynamic POLYGRAPH [53]	WISO	WISO	\mathbb{Q}^*	Del Freq IT Ph	Co [53]; Dec [53]; FuncDet [53]; Li [53]	0
ppSDF [54]	never	never	№*	ET Freq IT	Co [54]; Dec [54]; FuncDet [54]; Li [54]; StaSch [54]	0
VSDF [55]	never	never	ℕ*	IT PCI	Co [55]; Dec [55]; FuncDet [55]; Li [55]	0
HSDF ^a [56]	never	never	{1}	ET IT OOC	Co [49]; Dec [56]; FuncDet [56]; La [49]; Li [56]	0
ILDF [59]	never	never	N*	ET IT RaI	Co [59]; Dec [59]; FuncDet [59]; Me [59]; La [59]; Li [59]; StaSch [59]	0
VRDF [60]	WISO	WISO	N	ET IT Pa	Co [60]; SCo [60]; Th [60]; Me [60]	0
VPDF [61]	BISO	BISO	N	ET IT Pa Ph	Co [61]; SCo [61]; Th [61]; Me [61]	0
RMDF [64]	WISO + WIRO	WISO + WIRO	Q*	Del ET Freq IT Pa Ph	Co [64]; Dec [64]; ExecWin [64]; FuncDet [64]; Li [64]	o

Rate and topology updates acronym: BISO: Between Iteration Statically Oriented, WISO: Within Iteration Statically Oriented, WIRO: Within Iteration Runtime Oriented

Features acronyms: Del: Delay, ET: Execution Time, Freq: Frequency, IT: Initial Tokens, OOC: Out-of-Order Consumption, Pa: Parameters, PCI: Production and Consumption Instants, Ph: Phase, Ral: Rate as Interval *Analyzability acronyms*: Co: Consistency, Dec: Decidability, FuncDet: Functional Determinism, La: Latency, Li: Liveness, StaSch: Statically Schedulable, SCo: Strong Consistency

DF MoCC	Rate updates	Topology updates	Range rate	Features	Static analyses	Turing complete
BDF [65]	WISO	WISO	\mathbb{N}	IT	N/A ¹	•
IDF [65]	WISO	WISO	\mathbb{N}	IT	N/A ¹	٠
BPDF [66]	WISO	WISO	N	IT Pa	Co [66]; Dec [66]; Li [66]; StaSch [66]	0

 TABLE IV

 FEATURES AND STATIC ANALYSES OF BOOLEAN-BASED DF MOCCS.

¹ a subclass of BDF and IDF models are analyzable

Rate and topology updates acronyms: WISO: Within Iteration Statically Oriented

Features acronyms: IT: Initial Tokens, Pa: Parameters

Analyzability acronyms: Co: Consistency, Dec: Decidability, Li: Liveness, StaSch: Statically Schedulable

3) FSM-PSADF: Finite State Machine-based Parameterized Scenario-Aware Dataflow (FSM-PSADF) [73] enhances FSM-SADF by using parameters to improve the compactness. The scenario and its parameter configuration are both nondeterministically chosen at the end of an iteration. Reference [73] developed a state-space analysis to derive throughput and latency.

4) eSADF: eSADF [74] is a variant of SADF where negative exponential distributions govern the execution times of actors. This assumption permits the use of Markov Automatas (MAs) [75] to capture the semantics of eSADF. Analysis techniques of MA [76] yield a quantitative evaluation of memory footprint, throughput, or latency. Other metrics, such as the probability distribution of tokens in a channel, can also be computed. We assume that the authors of [74] consider only consistent and live eSADF specifications. The consistency and liveness can be checked using the same techniques as SADF since those do not depend on the execution time of the actors.

5) xSADF: Flexible Scenario-Aware Dataflow (xSADF) [77] extends both SADF and eSADF. Besides supporting actors' execution times that follow arbitrary probability distributions, xSADF endows actors with an additional cost function, e.g., energy usage, to have a finer analysis of the system's performance. Another extension is the process of selecting the scenario. In SADF and eSADF, scenarios follow a probabilistic distribution known at compile-time. xSADF relaxes this assumption and allows this choice to depend on external factors and possibly depend on runtime condition. This is why we consider that the rate and update topology of xSADF is WIRO instead of WISO as for SADF and eSADF.

F. Meta-Models DF MoCCs

This category includes DF MoCCs which can be applied on the top of another DF MoCC to extend its expressiveness.

1) PSDF: Parameterized Synchronous Dataflow (PSDF) [79] is a parametric meta-model applied to SDF. An actor of a PSDF specification is either *primitive* or *hierarchical*. A primitive one is composed of three graphs: the *init*, *subinit* and *body* graphs. The body graph models the actor's behavior, and the init and subinit ones handle parameter reconfiguration. In order to maintain a valuable

level of predictability, some parameter updates are restricted to occur at the boundaries of an iteration of the PSDF specification. The init graph handles such parameter updates, while the other is left to the subinit graph. An actor is hierarchical if its body graph is itself a PSDF specification. The authors of PSDF propose a quasi-static scheduling technique for acyclic PSDFs specification.

2) *PCSDF:* The authors of PSDF [79] also apply their method to CSDF and yield the Parameterized Cyclo-Static Dataflow (PCSDF). The parameterization of PCSDF is less expressive than VPDF: phases' ratios and sequence execution length are parameterized, while in VPDF, an additional parameter to each phase permits repetition a parametric number of times.

3) HPDF: Homogeneous Parameterized Dataflow (HPDF) [80] is a DF MoCC that refines a top-level actor of the HPDF specification using any DF MoCC with a well-defined notion of iteration, e.g., SDF, CSDF, or MDSDF. However, from our understanding of HPDF, top-level actors cannot be refined into a DF MoCC with timing constraints. There can be initial tokens between two actors of an HPDF specification. An HPDF specification executes in bounded memory if its actors execute in bounded memory.

4) *PIMM:* Parameterized and Interfaced Meta-Model (PIMM) [81] extends the semantics of any deterministic DF MoCC. The PIMM model uses an interface-based hierarchy and a set of parameters. Applying PIMM to SDF yields the Parameterized and Interfaced Synchronous Dataflow (PISDF), which can be seen as an extension of IBSDF.

5) SAD: State-Aware Dataflow (SAD) [82] tackles the memory persistence of initial tokens across the SAD's model iterations. SAD extends the semantics of the initial tokens with an explicit initialization/discard at the start/end of each iteration.

G. DF MoCCs with Enable and Invoke Capabilities

This category includes DF MoCCs where actors have two capabilities: *enable* and *invoke*. The *enable* capability determines if an actor can execute in a given mode, while the *invoke* capability performs the execution in that mode.

DF MoCC	Rate updates	Topology updates	Range rate	Features	Static analyses	Turing complete
SADF [67]	WISO	WISO	N	ET IT Pa	Co [67]; Dec [67]; La [68]; Li [67]; Me [68]; SCo [67]; Th [68], [78]	o
FSM-SADF [69]	BISO	BISO	N*	ET IT	Co [69]; Dec [69]; Me [72]; La [70]; Li [69]; Th [70]–[72]	o
FSM-PSADF [73]	BISO	BISO	N*	ET IT Pa	Co [73]; Dec [73]; La [73]; Li [73]; QSc [73]; Th [73]	o
eSADF [74]	WISO	WISO	N	ET IT Pa	Co [67]; Dec [67]; La [74]; Li [67]; Me [74]; SCo [67]; Th [74]	o
xSADF [77]	WIRO	WIRO	N	ET IT Pa	La [77]; Me [77]; Th [77]	0

TABLE V FEATURES AND STATIC ANALYSES OF SCENARIO-BASED DF MOCCS.

Rate and topology updates acronyms: BISO: Between Iteration Statically Oriented, WISO: Within Iteration Statically Oriented, WIRO: Within Iteration Runtime Oriented

Features acronyms: ET: Execution Time, IT: Initial Tokens, Pa: Parameters

Analyzability acronyms: Co: Consistency, Dec: Decidability, La: Latency, Li: Liveness, Me: Memory, SCo: Strong Consistency, Th: Throughput

DF MoCC	Rate updates	Topology updates	Range rate	Features	Static analyses	Turing complete
PSDF [79]	WISO	never	N*	Hi MM Pa	Co ¹ [79]; Li ¹ [79]; QSc ¹ [79]	N/A ³
PCSDF [79]	WISO	never	N	Hi MM Pa Ph	Co ² [79]; Li ² [79]; QSc ² [79]	N/A ³
HPDF [80]	BISO	never	\mathbb{N}^*	MM Pa	Co [80]; Li [80]; QSc [80]	N/A ³
PIMM [81] (PISDF)	WISO	WISO	N	Hi MM Pa	Co [81]; Li [81]; QSc [81]	N/A ³
SAD [82]	never	never	№*	IniDisIT MM	Same static analyzability as the underlying DF MoCC	N/A ³

TABLE VI FEATURES AND STATIC ANALYSES OF META-MODELS DF MOCCS.

 1 for a subclass of PSDF specification 2 for a subclass of PCSDF specification

³ those models are meta-model so we don't consider the turing-completeness

Rate and topology updates acronyms: BISO: Between Iteration Statically Oriented, WISO: Within Iteration Statically Oriented

Features acronyms: Hi: Hierarchy, IniDisIT: Initial and Discard of Initial Tokens, MM: Meta-Model, Pa: Parameters, Ph: Phase

Analyzability acronyms: Co: Consistency, Li: Liveness, QSc: Quasi-Static Schedule

1) EIDF: Enable-Invoke Dataflow (EIDF) [83] endows actors with two *capabilities* and a set of *modes*. Each mode defines a number of tokens to be produced and consumed. The *enable* capability asserts if an actor can execute in a given mode while the *invoke* capability performs the execution in that mode. Besides the number of produced tokens, the invoke capability returns the set of allowed modes for the subsequent execution of the actor. This set can be empty or contain a single or multiple elements. Especially, as multiple modes can be allowed for the next execution, an actor's behavior may differ depending on the arrival times of the tokens, and EIDF is non-deterministic.

2) *CFDF:* The invoke capability results in both the output tokens and the set of enabled modes for the subsequent executions. The Core Functional Dataflow (CFDF) [83] behaves the same as EIDF, except that the invoke capability returns a single mode, which makes CFDF deterministic. As the enable and invoke capabilities can be formulated to describe switch/select actors of a BDF model, EIDF and CFDF are also Turing-complete.

3) PSM-CFDF: Parameterized Set of Modes - Core Functional Dataflow (PSM-CFDF) [84] is tailored for CFDF when the number of modes grows significantly. Actors have a set of parameters, and a *configuration* is an assignation to those parameters. Modes with related functionalities are clustered together and denoted as Parameterized Set of Modes (PSM). The active PSM and the active configuration uniquely determine the mode for the actor executions. There are multiple next PSM that can be reached. As PSM-CFDF is not explicitly stated as deterministic, we assume that PSM-CFDF is non-deterministic.

4) *CF-PSDF*: Core Functional - Parameterized Synchronous Dataflow (CF-PSDF) [85] is a mix between PSDF and CFDF. A CF-PSDF actor has modes and three graphs: the ctrl graph, the subctrl graph, and the body graph. The ctrl and subctrl graphs have the same role as the init and subinit graphs of PSDF. The ctrl graph decides the execution mode and transmits the mode information to the ctrl graph of subsequent CF-PSDF actors. Two distinct actors can control a CF-PSDF actor. The first sends mode information to the ctrl graph, and the second sends data to the body graph.

5) *HCFDF*: Hierarchical Core Functional Dataflow (HCFDF) [86] specifies its actors as CFDF actors with a set of nested DFGs. Let H be an HCFDF actor. The nested DFGs match a subset of ports of H. An execution of H might be an invocation of a subset of the nested graphs, given that the dataflow interface defined by the mode is unchanged.

H. Process network-based DF MoCCs

This category includes dataflow formalism that generalizes the concept of DF MoCCs. This generalization is referred to as Dataflow Process Networks (DPNs).

1) KPN: Actors are sometimes called Dataflow Process (DP), and a network of DP is a DPN [88]. When a DP executes, it consumes tokens from its input channels and produces tokens on its output channels. A set of *execution rules* indicates

when the DP is *enabled* to execute. For instance, an actor of a SDF specification is enabled when it has enough tokens in its input channels, and an actor of an RMDF specification with a frequency constraint is enabled when it has both enough tokens in its input channels and when time is within its execution windows. Dataflow specifications we have studied so far are a particular type of Kahn Process Network (KPN) [2]. A KPN is a collection of concurrent processes that communicate with channels. In contrast with DP processes, KPN processes cannot test for the presence or absence of tokens in a given input channel. KPN processes are also *continuous* rather than discrete: there is no well-defined notion of the quantity of computation. Thus, input tokens are processed as soon as they are produced. A KPN is a deterministic system [2].

2) *RPN:* Reactive Process Networks (RPNs) [89] is an extension of KPNs where the set of active processes and channels may change at runtime on receiving events, which introduced non-determinism compared to KPNs. An RPN presents a static interface to the outside world that receives events and tokens. Events introduce non-functional determinism in the model.

VII. EXPRESSIVENESS AND ANALYZABILITY HIERARCHY

A. Protocol for Creating Expressiveness and Analyzability Hierarchy

The classification in the previous section can be used to quantitatively compare the expressiveness and analyzability of DF MoCCs. We call this the *expressiveness hierarchy* and the *analyzability hierarchy*. The protocol to create those hierarchies is the following, and they are also illustrated in fig. 1:

- 1) Characterize each DF MoCC according to the features described in section III and static analyzability described in section IV; this has been done in this paper (cf. table I to table VIII).
- 2) Assign a coefficient to each feature and static analysis according to the designer's need. Those coefficients aim to increase or reduce the importance of features or static analysis. For instance, coefficient 1 can be used for needed features and static analysis, and 0 for unneeded features.
- 3) Compute the expressiveness and analyzability score for each DF MoCC by summing the normalized features' score with the correct weighting, then sort DF MoCC regarding their expressiveness and analyzability score.
 - The score of boolean-valued features is 1 if the feature is present and 0 otherwise.
 - The score of range rate is 0 if it is {1}, 1 if N*, 2 if N, 3 if Q*, and 4 if Ω. The incrementation by 1 represents an increase in expressiveness.
 - The rate and topology updates score is computed in table IX. This score is the sum of the score of the rate updates and the topology updates. Each of them is evaluated as follows. If it is evaluated

DF MoCC	Rate updates	Topology updates	Range rate	Features	Static analyses	Turing complete
EIDF [83]	WISO	WISO	\mathbb{N}	N/A ¹	N/A	•
CFDF [83]	WISO	WISO	\mathbb{N}	N/A ¹	FuncDet [87]	•
PSM-CFDF [84]	WISO	WISO	\mathbb{N}	Pa	N/A	•
CF-PSDF [85]	WISO	WISO	\mathbb{N}	Hi Pa	N/A	•
HCFDF [86]	WISO	WISO	\mathbb{N}	Hi	N/A	•

 TABLE VII

 FEATURES AND STATIC ANALYSES OF DF MOCCS WITH ENABLE AND INVOKE CAPABILITIES.

Rate and topology updates acronyms: WISO: Within Iteration Statically Oriented Features acronyms: Hi: Hierarchy, Pa: Parameters

Analyzability acronyms: FuncDet: Functional Determinism

 $\begin{tabular}{ll} TABLE \ VIII \\ Features \ and \ static \ analyses \ of \ Process \ network-based \ DF \ MoCCs. \end{tabular}$

DF MoCC	Rate updates	Topology updates	Range rate	Features	Static Analyses	Turing Complete
KPN [2]	WISO	WISO	Ω^1	N/A	FuncDet [2]	•
RPN [89]	WISO	WISO	Ω^1	Hi	N/A	•

¹ any type of objects (pointers, integers, functions, etc.); the choice of "omega" is inspired from the probability theory where it represents the set of all possible outcomes *Rate and topology updates acronyms*: WISO: Within Iteration Statically Oriented *Features acronyms*: Hi: Hierarchy

Analyzability acronyms: FuncDet: Functional Determinism

as a single type, e.g., WISO for rate updates of POLYGRAPH, the score is the intersection of the type with itself on table IX, that is 6. Thus, the score for rate updates for POLYGRAPH is 6. If it is evaluated as two different types, e.g., WISO and WIRO for RMDF, the score is the intersection of the two types, that is 7. Thus, the score for rate updates for RMDF is 7.

TABLE IX Evaluation of rates and topology updates.

	never	BISO	BIRO	WISO	WIRO
never	0	1	2	3	4
BISO	1	2	3	4	5
BIRO	2	3	4	5	6
WISO	3	4	5	6	7
WIRO	4	5	6	7	8

B. Application of the Protocol

Let us assume that we are interested in specifying and analyzing CPSs with relaxed real-time constraints and modedependent execution. CPSs with relaxed real-time constraints have real-time constraints on only a subset of their processes, and CPSs with a mode-dependent execution have conditional execution branches. Thus, we are interested in the *Rate and* topology updates features to specify mode-dependent executions of CPSs as much as possible. Regarding specifying real-time constraints, we are interested in the features *Delay*, *Execution Time*, and *Frequency*. In addition, the features *Domain rate*, *Phase* and *Initial Tokens* are also interesting in easing the specification of real-time components with different frequencies.

Regarding the static analysis, let us assume that we want the DF MoCC to be *deterministic* and to provide a *consistency* and *liveness* analysis. The analysis of *execution windows* would also be of high interest.

The fig. 2 shows the expressiveness and analyzability score where we assign coefficient 1 for the features and static analyses of interest (as defined in previous paragraphs) of interest and coefficient 0 for the other. DF MoCCs shown in fig. 2 are the non-Turing complete and non-meta-model DF MoCC studied in this paper. We exclude Turing-complete and meta-model DF MoCC from this analysis as the static analysis of the former is limited, and the latter is not intended to be used on its own. We can see in fig. 2 that POLYGRAPH, Dynamic POLYGRAPH, TPDF and RMDF are the most suitable DF MoCC to specify and analyze CPSs with relaxed real-time constraints and mode-dependent execution

C. Extending the Classification

New features, static analyses, and DF MoCCs can be easily integrated into the classification system. A feature is introduced by defining how it is evaluated and evaluating each DF MoCC against this feature. A new static analysis



Fig. 1. Visualization of the protocol to compute the expressiveness and analyzability hierarchy.



Fig. 2. Expressiveness and analyzability score of DF MoCCs which are non-Turing complete and non-meta-model ones. The coefficient used to compute scores is 1 for the useful features and 0 for the unneeded ones.

is incorporated by specifying what it evaluates and evaluating each DF MoCC against this static analysis. A DF MoCC is added by characterizing it with the existing features and static analyses. Dependencies, whether among features or static analyses, can be seamlessly integrated.

D. A Visualization Tool

To enhance the accessibility of our classifiation system, we have developed an open-source visualization tool¹. This tool facilitates the comparative evaluation of DF MoCCs and enable system designers and researchers to filter DF MoCCs based on required features and static analyses. This contribution aims to support engineers and researchers in navigating the broad ecosystem of DF MoCCs.

VIII. CONCLUSION

We have presented a survey and a comparison framework for DF MoCCs found in the scientific literature. Our work includes a comprehensive list of features and static analyses designed to characterize the expressiveness and the analyzability of each DF MoCC. Building on this characterization, we proposed a protocol to assign expressiveness and analyzability scores to each DF MoCC according to system designer needs. The framework we proposed is easily extensible, allowing for the incorporation of new features, static analyses, and dataflow models. Our classification quantitatively supports a widely accepted assertion in the DF MoCC community: there is a trade-off between expressiveness and analyzability in DF MoCCs. The framework we proposed can serve both as a comparative tool and as a decision-making aid. We hope that the DF MoCC community will participate in this effort by providing feedback and by extending the classification system through the GitHub repository of the paper².

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